Emotional Contagion-Aware Deep Reinforcement Learning for Antagonistic Crowd Simulation

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Abstract—The antagonistic behavior in the crowd usually exacerbates the seriousness of the situation in sudden riots, where the antagonistic emotional contagion and behavioral decision making play very important roles. However, the complex mechanism of antagonistic emotion influencing decision making, especially in the environment of sudden confrontation, has not yet been explored very clearly. In this paper, we propose an Emotional contagion-aware Deep reinforcement learning model for Antagonistic Crowd Simulation (ACSED). First, we build a group emotional contagion module based on the improved Susceptible Infected Susceptible (SIS) infection disease model, and estimate the emotional state of the group at each time step during the simulation. Then, the tendency of crowd antagonistic action is estimated based on Deep Q Network (DQN), where the agent learns the action autonomously, and leverages the mean field theory to quickly calculate the influence of other surrounding individuals on the central one. Finally, the rationality of the predicted actions by DQN is further analyzed in combination with group emotion, and the final action of the agent is determined. The proposed method in this paper is verified through several experiments with different settings. We can conclude that antagonistic emotions play a critical role in the decision making of the crowd through influencing the individual behavior in the riot scenario, where individual behaviors are primarily driven by emotions and goals, rather than common rules. The experiment results also prove that the antagonistic emotion has a vital impact on the group combat, and positive emotional states are more conducive to combat. Moreover, by comparing the simulation results with real scenes, the feasibility of our method is further confirmed, which can provide good reference to formulate battle plans and improve the win rate of righteous groups in a variety of situations.

Index Terms—Crowd simulation, emotional contagion, antagonistic behavior, decision making, deep reinforcement learning

1 INTRODUCTION

With the rapid development of the global economy and the growth of urban population, the frequency and severity of emergencies continue to rise. These emergencies have the characteristics of uncertainty, suddenness, and harmfulness. Once the event occurs, it may cause serious harm to society and citizens, and even irreversible consequences, e.g., the riots. The term “riot” is widely used in the modern society to describe those associated events of violation and destruction and regarded as a sign of defiance against a central authority or serious conflict between opposing groups. According to the nature of conflict, degree of involvement, and severity of the conflict, it can be classified into small-scale riots or large-scale revolutions such as civil wars and race wars[1]. For example, in August 2011, a demonstration in London suddenly turned into a violent confrontation[2].

where criminals attacked the police, innocent people, and destroyed public property. In September 2020, in Kentucky, the United States, due to conflicts between demonstrators from two different camps, the two sides gathered in public venue to confront and provoked each other, which aroused social concern. There are more and more similar sudden crowd incidents. The harm and losses caused by each incident are incalculable and shocking. How to enable relevant departments to efficiently resolve such incidents has become a matter of great concern to all society, and it is also a key issue that many scholars have devoted themselves to solve.

As an important research direction in the computer graphics community, crowd simulation has been widely used in many fields such as security management, military exercises, and traffic planning. Especially in the face of riots, this kind of methods is often used to help simulate the corresponding process, which will save a lot of public resources compared to traditional solutions, such as manual exercises. By modeling and simulating the evolutionary process of crowd movement, it is possible to have more detailed understanding of the riots and their trend under emergencies, to truly reproduce such crowd behaviors. Then, we can quickly analyze and formulate effective decisions to quell the incident and reduce the potential loss. In the war game, researchers often deploy combat decisions in this way[3], [4], [5]. However, in sudden real riots, there are many factors playing different roles when the crowd fights happen, and the emotions affect the antagonistic behavior in the group to a large extent in the way of decision-making.
of crowd behaviors[1], [6]. For example, what distinguishes the mob from the audience is their emotional, irrational, and psychological homogeneity[7]. Emotions are easily contagious and spread among the crowd, especially the instinctive emotions of human beings. The special riot scenario itself is irrational and impulsive, where the crowd is more easily to be dominated by the antagonistic emotion. This is a typical psychological state of different individuals in crowd violence scenes. Therefore, when planning antagonistic crowd behaviors, emotional factors must be incorporated into the crowd simulation model carefully.

In another aspect, individuals in antagonistic groups need to quickly make decisions in complex and changeable environment, and it is difficult for individuals to get effective real riot scene dataset from similar events in the past. Although the existing crowd simulation models have considered the emotional factors when planning behaviors, it is not quite reasonable to design the overall movement trend and specific behaviors of the agent in advance at the same time, and the formulated behaviors may deviate from the real cases. Recently, deep reinforcement learning that combines the perception capabilities of deep learning and decision-making capabilities of reinforcement learning have been widely explored. Many researchers try to use this novel technique to study the decision-making behavior of the crowd simulation [8], [9]. However, when using this method to model the crowd behaviors, the attributes of agents, such as the inherent group emotions, are not fully considered. The constructed simulation model lacks authenticity, and the win rate of the righteous side is not high enough during the battle.

To achieve satisfactory simulation results, we also summarize five principles for the riot simulation, including variability, interactivity, complexity, practicality and infectivity.

- Variability: The emotional differences of individuals in the crowd should be fully considered.
- Interactivity: The interaction process of confrontation between the righteous side and the opposite side should be explored, and also the entire evolution.
- Complexity: Riot simulation needs to consider multiple influencing factors, such as the environment and emotional contagion among agents.
- Practicality: The results of the riot simulation system should be very similar to the actual situation.
- Infectivity: The emotion is easily contagious and spreads among the antagonistic crowd.

To solve the above problems, this paper proposes an antagonistic crowd behavior simulation model (ACSED) integrating emotional contagion into deep reinforcement learning. First of all, we fully consider the key role of emotions on antagonistic crowd behaviors. The antagonistic emotional contagion module is built based on the improved SIS model, and combines with specific combat situations to estimate individual emotions (Section 3.2). Then, we use deep reinforcement learning to construct antagonistic action predict module for different groups, allowing the agent to learn decision-making action efficiently and autonomously, and leveraging the mean field theory[10] to simplify the calculation complexity (Section 3.3). Finally, we combine with the emotion of each agent in the crowd to judge whether the learned action is reasonable, and the final battle is determined according to the action rules of agent under different emotional states (Section 3.4).

The simulation experiments prove that the proposed method is helpful for studying the antagonistic behaviors in the riots, and able to formulate more realistic and reasonable combat plan for the righteous group and improve the win rate. The main contributions of this paper are as follows:

- We propose an emotional contagion-aware deep reinforcement learning model for antagonistic crowd simulation (ACSED). The DQN and mean field theory are introduced to predict the action in the crowd. The proposed model can provide the agents with more reasonable and effective actions.
- We introduce an antagonistic emotional contagion module to calculate individual emotions and formulate the behavioral rules of agents under different emotions. This module fully considers the influence of emotions on the intensity of the attack. We establish a connection between the individual’s emotions and the suffered harm to improve the authenticity of the simulation.
- We develop an antagonistic action prediction module to estimate the potential action for each agent in the crowd. Meanwhile, the emotion of the agent is used to further analyze whether the predicted action is reasonable. Emotion combines with the predicted action to determine the final action better.
- Our model is able to improve the win rate of the battle in crowd antagonistic scene efficiently, and fully explores the advantages of the emotion to win more with less, which is more in line with the realistic cases.

The rest of this paper is organized as follows. The second section discusses the related work involved in this paper. The third section proposes the antagonistic crowd simulation model. The rationality of the proposed model is verified through different experiments in the fourth section. Finally, the conclusion including a summary and future work is demonstrated in the last section.

2 RELATED WORK
2.1 Crowd Simulation
Crowd simulation [11] is of great significance to many fields and is widely used in the scenes such as public safety, military training, and video games[12]. It can be generally divided into macro models and micro models [13]. Macro models regard the crowd as a whole, focusing on the movement trends of the whole crowd. The details of individual movement is relatively rough[14], [15], [16]. Representative methods include aggregate dynamics models [17], potential field models [18], and so on. Micro models pay attention to the concrete details of individual movement in the crowd, studying their behavioral rules and decision-making process. This kind of model can more realistically show the complex interactions among individuals, which is also used in this paper.

Classical microscopic models include cellular automata model [19], social force model [20], multi-agent model [21] and so on. Ren et al. [22] proposed a combined multi-agent model and data-driven approach for heterogeneous group simulation, where they estimate crowd motion states from a real dataset including position, velocity, and control direction.

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information. Chao et al. [23] proposed a calibrated force-based model for mixed traffic simulation, which includes the simulation of traffic flow and crowd. They used force-based approach to simulate the complex behaviors and interactions of various road users. Liu et al. [24] proposed a velocity-based and data-driven optimization framework to build dynamic crowd simulation. They solved the motion selection problem by finding the optimal speed from a real-world crowd movement dataset. Sahil et al. [25] inferred user intent based on the observed proxemics and gaze-based cues. The inferred intent is used to guide the response of the virtual agent. It also can generate locomotion and gaze-based behaviors in shared avatar-agent virtual environments. Recent years, plenty of researchers have devoted themselves to the simulation of crowd emergency or riots with emotion factor. Beltaief et al. [26] proposed a multi-agent simulation model based on psychological theory, which was able to simulate the crowd gathering phenomenon more realistically. Spartalis et al. [27] used cellular automata to simulate pedestrian movement. They introduced group categorization and guidance attributes to help study the influence of guidance on the crowd evacuation. The crowd is categorized according to emotion and a special group has leadership characteristics. Pax et al. [28] built an agent-based architecture, which allows for the efficient simulation of indoor scene without losing the ability to specify rich and heterogeneous agent behaviours. With the rapid development of multi-agent deep reinforcement learning [29], researchers begin to use this novel tool to model the complex action of agents, especially for emergencies. This kind of method can estimate actions in a closer way to human thinking, which is more reasonable and reliable than previous methods. In detail, DQN is to score the actions of each agent, and then selects the actions which have the most positive impact on future earnings. This training process of trial and error is closer to human thinking. Gupta et al. [30] used the multi-agent deep reinforcement learning to explore the cooperative strategy learning problem by the complex and partly observable agents. By designing a set of experiments for cooperative control tasks, the effectiveness of their method was proved. Zhang et al. [31] proposed a data-driven crowd evacuation framework based on hierarchical deep reinforcement learning. In the micro-control layer, the track sequence learned in the macro-control layer is used as the motion target, and the multi-agent deep reinforcement learning method is used to learn the collision-free motion velocity of the individual.

Although the crowd simulation has made great progress up to now, they still face enormous challenges to simulate the antagonistic crowd behaviors. One of the most important reasons is that the antagonistic behaviors are more complex and can be easily changed by unstable emotion, which bring great challenges to plan accurate agent actions in advance based on previous experience. In another aspect, although the usage of multi-agent deep reinforcement learning allows agents to learn action efficiently, this novel technology has not involved the inevitable emotion factor in crowd simulation, and the authenticity of simulation still needs to be improved.

### 2.2 Emotional Contagion

Emotion is a short-term psychological state produced by individuals based on subjective cognition, which is closely related to feelings, thoughts, and actions [32]. Individual emotion plays a vital role in the process of their behavioral decision-making [33]. The emotional cognitive theory believes that emotions arise from an individual’s evaluation of something that is beneficial or harmful to oneself [34]. Emotional contagion is one very typical and essential factor in the crowd movement. Therefore, during the crowd simulation, we should not only pay attention to the emotional state of the individual, but also need to study the process of emotional contagion[35]. Emotional contagion methods are mainly divided into two categories. One is based on thermo-dynamic methods [36] and the other is based on epidemiological methods [37]. The epidemiological methods are inspired by the spreading mechanism of epidemic diseases, where susceptible persons are at risk of being infected when they come into contact with infected one.

Hill et al. [38] proved that the epidemic model can be used to study the problems related to emotional contagion in the population. They introduced a new form of the classic SIS (Susceptible Infected Susceptible) model that includes the possibility of “spontaneous” (or “automatic”) infection, termed the SISa model. On the basis of this work, Liu et al. [39] proposed S0Ssa-SPSa model, with divided crowd emotions into positive and negative states, and further studied the internal mechanism of emotional contagion. Nizamani et al. [40] constructed an emotional contagion model based on the spreading epidemics models, divided the population into five categories, and studied the spread of anger among groups. Zhang et al. [41] proposed a method to optimize positive emotional contagion in crowd evacuation through introducing the role of safety officer to maximize the “calm-down” effect of the crowd. Varni et al. [42] further explored the primitive emotional contagion of agents in dyadic interactions, which is defined as the tendency of people to automatically mimic and synchronize their multimodal behavior in interactions, resulting in emotional convergence. Zhao et al. [43] constructed an improved SIRS model to study the spread of panic in subway passengers, and analyzed in detail the influence of crowd density and individual psychology on group emotions. Mao et al. [44] proposed one crowd simulation approach involving the OCEAN personality model and the OCC emotion model, and combined the CA-SIRS emotional contagion model, to simulate diverse crowd behaviors. Li et al. [45] proposed a crowd antagonistic behavior simulation model (ACSEE) by combining antagonistic emotions and evolutionary game theory. They used cellular automata to determine the position of the agent, and simulated similar antagonistic crowd behavior in real scenes. Mao et al. [46] proposed a unified framework to simulate emergency evacuation in virtual environments. The emotional contagion in their work is considered from three aspects: intra-group contagion, inter-group contagion and emotional contagion based on the third-party authority. Xu et al. [47] proposed a novel approach for crowd evacuation simulation by modeling panic generation and contagion in multi-hazard situations.

Inspired by above work, aiming at the spread of emotions between groups in the outbreak of sudden riot, we build an antagonistic emotional contagion module based on the improved SIS model. We explore the influence of
emotions on antagonistic crowd behavior, and formulate more realistic actions of each agent in the crowd.

2.3 Deep Reinforcement Learning

In recent years, deep reinforcement learning (DRL) has become an important research direction in the field of artificial intelligence[48]. It is widely used in many important areas such as behavioral decision making, robot control, parameter optimization, etc. DRL integrated deep learning with Reinforcement Learning (RL) to partially overcome the curse of dimensionality. DeepMind proposed the DQN algorithm [49], which combined Q-learning with deep learning together. The state and action were regarded as the input of deep neural network. Wang et al. [50] proposed an improved multi-agent reinforcement learning method, combining with an improved social force model in crowd evacuation simulation. Toghiani-Rizi et al. [51] evaluated the ability of three deep reinforcement learning algorithms to learn the tasks in simulated ground combat scene, proving that deep reinforcement learning has the potential to improve practices and techniques for modeling tactical behavior. Yang et al. [9] combined Q-learning and mean field theory to propose the Mean Field Q-learning (MF-Q) algorithm, which was dedicated to solving the problem of large-scale agent learning with higher calculation efficiency. In detail, when they calculated the influence on certain agent, a mean value was introduced to replace the effect of all other agents, which greatly simplified the increasing model space due to the increase of the number of agents. The effectiveness of the MF-Q algorithm is verified in a simple crowd antagonistic scene and can guarantee the win rate of group battles.

However, original DRL-based algorithms do not fully consider complex factors that affect individual actions in different groups, such as emotions. Compared with existing riot simulation systems, reinforcement learning methods have obvious advantages. When the traditional riot simulation systems model individuals, they mostly initialize the emotional values according to a unified standard, which ignore individual differences. In fact, there are often some core fighters and bystanders in the riots. In another aspect, most of riot simulation systems are simulated by rules, such as using social force-based methods or velocity-based methods. These rules also limit the effect of simulation [52], [53], [54]. In this paper, we try to improve the work of [9]. We build a new simulation model of antagonistic crowd behavior, which integrates emotions with multi-agent deep reinforcement learning.

3 ANTAGONISTIC CROWD SIMULATION MODEL

This paper mainly studies the riots and proposes an emotional contagion-aware deep reinforcement learning model for antagonistic crowd simulation. We define the side that provokes the riot as the opposite side, and the side that calms the situation as the righteous side. By studying the characteristics and laws of crowd movement in riot scenes, we can formulate reasonable and efficient decision-making actions for the righteous group and improve their win rate.

The framework of the antagonistic crowd behavior simulation model is shown in Fig. 1. First, based on the improved
SIS model, we combine with the combat situation to build an antagonistic emotional contagion module to calculate the emotions of different groups in emergencies. Then, we propose an antagonistic action prediction module based on DQN and mean field theory. We use these novel tools to reasonably analyze and predict the agent action in the crowd. Finally, the final action of the agent is determined according to the action rules under different emotional state. The method proposed in this paper helps to study the antagonistic behavior of the crowd under violent and terrorist incidents, so as to formulate more conducive action plans for the righteous group.

### 3.1 Assumptions

There are many complex factors causing the antagonistic crowds. It is impossible to consider all the factors for the simulation of antagonistic crowd. Based on the observations of the behaviors of antagonistic crowds, we propose the following assumptions to make this problem solvable.

- The emotions of the opposite side in the riot are quantifiable, and the emotions are divided into three types: positive, neutral and negative. The emotions of each side can affect the emotions of teammates and the opposite side.
- The perception range of an agent is limited and configurable.
- The actions of individuals in antagonistic crowd are separated into movement actions and attack actions.
- If the agent dies, it will no longer pose a threat, nor it will affect the emotions of the surrounding agents.
- The battle is limited between two groups.

### 3.2 Antagonistic Emotional Contagion Module

The current methods based on deep reinforcement learning to model antagonistic crowd behavior do not fully consider the emotional factors of the individual and there are some disadvantages such as deviations between the simulation results and the ground truth, and the unsatisfactory action. To solve the above problems, we build an emotional contagion module which is more suitable for confrontation scene. This module is based on the improved SIS model and combines with the combat situation to analyze the specific effect of emotions on antagonistic crowd behavior. The decision can be more realistic, reasonable and credible.

The emotion of the individual is classified (negative, positive, neutral). According to the warehouse model in the epidemic model, the population is divided into susceptible and infected. $E_i$ represents the emotion intensity of $Agent_i$, which is set in the range $[0,1]$ for the righteous side and $[-1,0]$ for the opposite side. The larger the emotional value of both groups, the more positive they are, on the contrary, the smaller the more negative. When it is close to the median value of 0.5 or −0.5, it means that $Agent_i$ is in a neutral state. For different types of agents, the more positive the emotional state of the righteous side, the more daring to take offensive action to subdue the opposite side. On the contrary, they will fear the opposite side and fight passively. The more negative the emotional state of the opposite side, the more inclined to challenge the righteous side and will attack them actively.

Emotional contagion between groups is similar to the spreading process of infectious diseases. Individual emotions will not only be affected by other people in the environment, but also by their own. Therefore, we calculate the agent’s emotion from the external environment and self evaluation. The first part is the external influence $E_i^{ex}$. The influence of the external environment comes from two sources. One is the distance between $Agent_i$ and surrounding agents. The other is the emotions of surrounding agents. The second part is the self-influence $E_i^{sc}$. The influence of self-assessment refers to the influence of the behavioral value assessment obtained by $Agent_i$ on its emotions. According to the emotion cognitive evaluation theory, emotions are generated from the evaluation of some specific aspects between the individual and environment, thereby generating an adaptive response to the current situation. The calculation of emotional contagion is shown in Formula (1):

$$E_i = E_i^{ex} + E_i^{sc}. \quad (1)$$

First, we calculate the amount of changes in the emotion of $Agent_i$ after being affected by the external environment, that is, when $Agent_i$ interacts with other agents around it, it will be affected by the emotions of other agents. Inspired by [55], the changing values of emotional contagion of $Agent_i$ is defined in Formula (2):

$$\Delta E_i^{ex}(t) = \left[1 - \frac{1}{1 + \exp(-D)}\right] \times E_i(t) \times A_{ij} \times B_{ij}, \quad (2)$$

where $D$ represents the distance between $Agent_i$ and other $Agent_j$, $E_i$ represents the emotion of $Agent_i$, $A_{ij}$ is the intensity of emotion received by the affected $Agent_i$ from the influencing $Agent_j$, and $B_{ij}$ refers to the emotional intensity sent from $Agent_j$ to $Agent_i$. The external emotional contagion is the result of the contagion of the righteous and opposite agents in the perceiving range on $Agent_i$. People who belong to the same team as $Agent_i$ will have a positive effect on their emotions, otherwise they will have a negative effect. We have to calculate the external emotional contagion of the righteous side at time $t$, which is formulated as

$$\Delta E_r^{ex} = \sum_{i=1}^{m} \Delta E_{r,t_i}^{ex}(t) + \sum_{j=1}^{n} \Delta E_{r,o_j}^{ex}(t). \quad (3)$$

Similarly, the formula for calculating the external emotional contagion of the opposite side is:

$$\Delta E_o^{ex} = \sum_{i=1}^{n} \Delta E_{o,t_i}^{ex}(t) + \sum_{j=1}^{m} \Delta E_{o,o_j}^{ex}(t). \quad (4)$$

When we calculate the emotional state of one agent, it is necessary to consider the influence of the agent on the emotions of itself and others after taking actions. Inspired by [45], [56], we calculate the influence of self-evaluation on the emotion of the agent based on the reward value in reinforcement learning. During the battle between two groups, the agent will obtain the corresponding reward value after taking the action, which is used to evaluate the performance of the agent. The mental emotion calculation method is as follows:
\[ \Delta E_i^e(t) = 0.1 \times \left( \frac{1}{\delta + \exp(r_i(t)/\gamma)} \right), \quad r_i(t) \geq \gamma, \]  
\[ \Delta E_i^m(t) = -0.1 \times \left( \frac{1}{\delta + \exp(r_i(t)/\gamma)} \right), \quad r_i(t) \leq -\gamma, \]

where \( r_i(t) \) represents the difference between the reward values of two consequent time steps, \( \delta \) is an empirical parameter. When \( r_i(t) \in (-\gamma, \gamma) \), the action of \( \text{Agent}_i \) has less effect on its emotions and can be ignored. When \( r_i(t) \geq \gamma \), it means that \( \text{Agent}_i \) performs the action to promote the battle result. If \( \text{Agent}_i \) is righteous, its emotions will become positive, otherwise if it is opposite, it will become negative. When \( r_i(t) \leq -\gamma \), it means that the action performed by \( \text{Agent}_i \) is not conducive to the current combat situation. If \( \text{Agent}_i \) is positive, its emotions will become negative, and if it is negative, it will become positive. We calculate the emotional contagion of \( \text{Agent}_i \) according to Formula (5)(6).

At time \( t \), the emotional value can be calculated by the following formula:

\[ E(i, t) = E(i, t-1) + \Delta E_i^e(t) + \Delta E_i^m(t). \]  

The emotional value of \( \text{Agent}_i \) at time \( t-1 \) is summed with the increase in emotional contagion obtained by \( \text{Agent}_i \) at time \( t \).

### 3.3 Antagonistic Action Prediction Module

In this section, we build an action prediction module based on DQN and mean field theory, which is able to calculate the antagonistic action taken by one agent efficiently. There are two important reasons for choosing DQN. On the one hand, riots are usually sudden and have different types, and it is difficult to accumulate experience from past events. DQN is suitable for solving such problems with less prior knowledge. On the other hand, DQN belongs to the off-policy model with experience playback pool, which can break the correlation between existing data and realize a more stable learning process. At the same time, the usage of convolutional neural network as a value function can fit the Q table in the Q-learning algorithm better.

The overall pipeline of this module is as follows. First, the two sides use the action provided by the initial network to fight against each other, and the sampled data will be stored in the experience replay pool. Then, we randomly sample data from the experience replay pool to train the network and iterate for many rounds. Finally, the trained model is used to predict the initial action of each agent.

The specific network structure is shown in Fig. 2. input_1 is used as the input of the first convolution layer, which contains information about the categories of other agents within the perceiving range of each agent. Then, the output of two convolutional layers is input to the first fully connected layer. input_2 is used as the input of the second fully connected layer, which contains information such as ID information, location, action, and emotional value. input_prob is the mean action, and we input it into the fully connected layer. The Q value is obtained through the output layer, and the decision-making action of the agent at the next moment is determined according to the Q value.

The mean action mentioned above is calculated using mean field theory. Due to the large number of agents involved in riots, the calculation complexity must be simplified while constructing the corresponding network [9]. Inspired by [27], we approximate all the influence of the neighboring agents as one influence, and the actions of the neighboring agents as an action.

The dimension of joint action \( a \) grows proportionally with the number of agents \( M \). Since all agents act strategically and simultaneously to evaluate their value functions based on joint actions, the learning of standard Q-function \( Q(s, a) \) becomes infeasible. To solve this problem, we factorize the Q-function using only pairwise local interactions. \( Q(s, a) \) can be calculated by the following formula:

\[ Q_i(s, a) = \frac{1}{M} \sum_{k \in M(i)} Q_i(s, a^i, a^k), \]  

where \( M(i) \) represents the index set of the neighboring agents of agent \( i \) with the size \( M = |M(i)| \). \( a^i \) is the action taken by \( \text{Agent}_i \) in the state \( s \), and \( a^k \) represents the actions of other neighboring agents. The action of one agent and that of its neighbors can be combined as an action pair in Formula (8). The pairwise approximation of agents and their neighbors not only reduces the complexity of interactions among agents, but still implicitly preserves the global interactions between any pair of agents [57].

The \( Q(s, a^i, a^k) \) in Formula (8) can be approximated using the mean field theory. When calculating the agent action at time \( t \), the action estimated by DRL network at time \( t-1 \) will be considered. The action of \( \text{Agent}_i \) is a discrete action categorical variable represented by one-hot encoding. Through the action coding of the neighborhood agents, their mean action can be obtained by the formula:

\[ a^k = \bar{a}^i + \delta a^{i,k}, \quad \text{where} \quad \bar{a}^i = \frac{1}{M} \sum_k a^k, \]  

where \( \bar{a}^i \) represents the mean action, \( \delta a^{i,k} \) is a small fluctuation value. In this formula, the Q function of \( \text{Agent}_i \) can be shown in the following formula:

\[ Q_i(s, a^i) = \frac{1}{M} \sum_{k \in M(i)} Q_i(s, a^i, a^k) = Q_i(s, a', \bar{a}^i). \]
The behavioral tendency of agents in different situations is shown in Table 1. If the agent is in an aggressive state, both the righteous and the opposite sides will be more proactive in taking offensive actions and attacking the opponent. At this time, the righteous agents have positive emotion, while the opposite side will be negative. If the agent is in a conservative state, it means that the current state is not active. The agent only has a defensive mindset and prefers to adopting move-type action. At this time, the righteous side has negative emotion, while the opposite side will be positive. The positivity of the emotion of the opposite side is reflected in the weak combat consciousness.

**Algorithm 1. ACSED Algorithm**

1: Initialize the attributes of Agent, such as ID information id, location pos, action act, emotional value emo, mean action act_learn, environmental awareness view;
2: Initialize max time step $t = 400$, discount rate $\gamma = 0.95$, learning rate $\alpha = 1e-4$, batch size $bs = 256$, memory size $ms = 2^{10}$;
3: while $t < 400$ do
4: if the size of any one team $live < 2$ then
5: break
6: else
7: Enter the parameters into the network to estimate the Q value;
8: Predict the action $act_p$ based on the maximum Q value;
9: Update pos, view, and calculate the rewards $r$;
10: Obtain the agent’s final decision-making action $act_f$ through specific action rules;
11: Calculate the mean action $act_{mean}$ at next time step $t'$ according to the action $act_f$ of the agent;
12: Update the emotional value $emo'$ of the agent at next time step $t'$ based on following function: $E(i, t') = E(i, t) + \Delta E_{emo}(t') + \Delta E_{emo'}(t')$;
13: end if
14: end while

We analyze whether the action predicted by the DRL network is reasonable according to the emotional state of the agent, so as to determine its final action. If the predicted action of the agent is unreasonable, it will adversely affect its own battle situation. Therefore, it is necessary to re-plan more advantageous actions according to the agent’s combat state. As shown in Table 1, the actions of the agent are divided into two categories, including the move action and attacking one. The detailed discussion will be divided into the following situations.

First, if the action predicted by the network for Agent, belongs to the type of attack, the rationality of the action needs to be analyzed based on its current combat state and attack target.

**If Agent, is currently aggressive:**

- The target of Agent, is a blank location or wall. Such an attack target is meaningless, so Agent, will choose another conservative agent to attack from nearby reachable targets. If there are multiple eligible agents, the closest agent will be selected.
- The target of Agent, is the opposite Agent,. First, the emotional value of Agent, and that of the attack target will
be compared. If $|E_i| > |E_j|$ or $||E_i| - |E_j|| < E_{th}$ ($E_{th}$ represents the emotional threshold), $Agent_i$ will execute the predicted action; if $|E_i| < |E_j|$ and $|E_i| - |E_j|| > E_{th}$, it is necessary to determine the number of partners and that of opponents within the perceiving range of $Agent_i$. If the number of partners is less than that of opponents, the $Agent_i$ will choose the action corresponding to the largest Q value in the move-type. If the number of partners is more than the opponent, the agent with the smallest absolute emotional value in the opponent group will be attacked. If $Agent_i$ is currently conservative:

- **The attack target of $Agent_i$ is a blank location or a wall.** $Agent_i$ will choose an action with the largest Q value among the move-type actions.

- **The target of $Agent_i$ is the opposite agent.** We compare the emotional value of $Agent_i$ and that of the attack target. If $|E_i| > |E_j|$ or $||E_i| - |E_j|| < E_{th}$, we execute the attack action. If $|E_i| > 1/2T$, the attack action corresponding to the second largest Q value in the attack-type will be taken, and the attack target will be changed. If $|E_i| < 1/2T$, $Agent_i$ will choose an action with the largest Q value among the move-type actions.

Second, if the network predicts that the next action of $Agent_i$, belongs to the type of move, it is necessary to discuss the rationality of the action based on the current state of $Agent_i$ and the surrounding environment.

- **If $Agent_i$ is currently aggressive.** We compare the emotional value of $Agent_i$ with that of all opponents within its perceiving field. If all opponent members within the perceiving range are more aggressive than $Agent_i$, then they will execute the move action.

- **If $Agent_i$ is currently conservative.** It performs the predicted action.

In addition, we also consider the effect of opponent’s emotion on the damage suffered by $Agent_i$. In fact, the attack intensity highly depends on the corresponding emotion when the agent takes offensive action. The more aggressive the combat state, the stronger the attack, and the damage received by $Agent_i$ after being attacked increases with the strength of the attack. Therefore, we associates the emotion of the agent with its health value based on above facts. When modeling crowd behaviors, the attributes of the agent are set based on the actual situation to ensure that the calculation results are in line with reality and increase the practicability of the model. Specifically, according to the emotional value when the agent takes the attack action, the damage of the attacked target is calculated, as shown in Formula (15):

$$Hp_j(t) = Hp_j(t - 1) - \beta \log \left(1 - |E_j(t - 1)|\right),$$

(15)

where $E_j(t - 1)$ represents the emotion of $Agent_i$, $\beta$ is an empirical coefficient, which is specifically set according to the experimental results. If $Agent_i$ is righteous, the more positive the emotion, the greater the intensity of the attack, and the more harm the attacked individual will suffer. If $Agent_i$ is the opposite side, the more negative the emotion, the greater the intensity of the attack, and the more harm the attacked individual will suffer. $Hp_i(t - 1)$ represents the health value of $Agent_i$ at time $t - 1$. When $Hp_i \leq 0$, the $Agent_i$ is subdued and does not have combat capability.

## 4 Experimental Results

Our experiment is implemented on Intel CPU i7-8700K, 3.70 GHz, 32GB memory, Linux operating system environment. C++ and Python language is used to realize the antagonistic crowd behavior simulation model. We verify the proposed method on MAgent, a multi-agent reinforcement learning platform that supports hundreds to millions of agents. The battle game in MAgent is a mixed competitive competition scene. In a pre-defined grid world, two groups of agents are fighting against each other, whose actions are provided by the same or different algorithms. The goal of both groups is to defeat the other, and the group with more remaining agents wins. In each experiment, the two sides play against each other for 50 rounds, and the final outcome is determined based on the win rate. The results of one round will be randomly selected for visualization. Through multiple sets of different experiments, we deeply explore the relationship between emotion and win rate, and prove the effectiveness of the proposed method. Then, the feasibility of the method is further verified by comparing the simulation results with the real scene. And we visualize the results in Unity3D.

### 4.1 Comparison of the Win Rate of Both Sides

#### 4.1.1 Two Sides With Different Emotional States

The experiments in this section mainly analyze the influence of the emotion of agents on the battle results for the two sides. Both sides use the same proposed algorithm to provide actions, and the initial number of agent is 256. The initial emotional values in our simulation system mainly come from the analysis of relevant materials such as riot videos according to the novel OCC model[33]. We set up three sets of experiments to verify the fighting results of the agents under different emotions. In the first set of experiments (A1), the initial emotions of the opposite side are neutral, and the initial emotions of the righteous side are controllable variables that can be classified as positive, negative or neutral. In the second set of experiments (A2), the initial emotions of the opposite side are positive, and the initial emotions of the righteous side are the same as the A1 setting. In the third set of experiments (A3), the initial emotions of the opposite side are negative, and the initial emotions of the righteous side are also consistent with A1. Under different emotional states, we randomly assign initial emotional values to each agent. The results of this part of the experiment demonstrated the validity of positive emotions.

Fig. 3 shows the battle results of two sides with different emotional states. The experimental parameters are shown in Table 2. The second column in this table is the number of agent on the righteous side and that on the opposite side. The third column is the initial emotional state. $T$ in Table 1 is set to 0.5. According to the results with A1-1 experimental
setting, when other conditions and emotional states are the same, the win rate is basically close. In A1-2 setting, since the emotional state of the righteous side is more aggressive than that of the opposite side, the win rate is 0.64, winning 32 rounds. In A1-3 setting, the opposite side achieves a win rate of 0.58. The agents in the righteous group have a negative emotional state and are afraid of the opponent and dare not attack actively. During these experiments, the sum of the win rates of both groups is not 1.0, it means that there are some draws. In Experiment A2-2, when the emotions of both sides are positive, the winning rate of the righteous side is higher than that in Experiment A1-2. In Experiment A3-3, since the opposite side is more aggressive than the righteous side, the opposite side gets more victories.

From the experiment under A1-2 setting, we randomly select to visualize one round battle, as shown in Fig. 4. In this setting, both sides are positive, which means that the righteous side is more aggressive than the opposite side, and will actively attack the opponent. It can be seen from Fig. 4 that a small number of agents choose to retreat and be away from their group in the red box. These agents perceive the strong positive emotions of the righteous side. They choose to retreat to avoid being hurt. They are afraid of the opponent and are unwilling to attack the opponent, therefore most of them are floating on the edge of the scene.

The result proves that when the righteous side is fighting the mob, it should have positive emotions and maintain the enthusiasm for combat. In an aggressive combat state, the agent will be more inclined to take offensive actions, which has a greater probability of subduing the opponent. This can improve the combat win rate to a certain extent.

4.1.2 Two Sides With Different Algorithms

In this section, we compare our algorithm with the MF-Q [9] algorithm and our previous ACSEE [45] algorithm. We compare the win rate of the ACSAE with the original MF-Q algorithm, and then, the ratios of the remaining numbers of the two sides of the three algorithms under the same conditions are compared. When other experimental conditions are the same, we try to figure out which algorithm the group adopts will have a higher battle win rate. At the same time, the rationality and reality of the simulation results of the three algorithms are judged.

To compare win rates with the original MF-Q algorithm, we set up three sets of experiments. The righteous side uses the algorithm proposed in this paper, the agent can perceive the emotions of itself and others, and they can plan their actions based on the information they perceive. The opposite side uses the MF-Q algorithm, planning action without considering individual emotional factors. The agent does not have emotional attributes and will not be able to perceive relevant information.

The results of the three sets of experiments are shown in Fig. 5. In the B1 experiments, the emotional state of both groups is the same. Three comparative experiments are conducted for different emotional states of neutral, positive and negative. The mean value of the three experimental results are calculated. The results show that the proposed algorithm in this paper is better than the MF-Q algorithm. The win rate is higher. In the B2 experiments, the emotional state of both groups is positive, that means the righteous side is more aggressive. The results of the match are shown in the B2 experiments of Fig. 5. The righteous side has a win rate higher than the MF-Q algorithm. The results show that the proposed algorithm in this paper is better than the MF-Q algorithm. The win rate is higher. In the B2 experiments, the emotional state of both groups is positive, that means the righteous side is more aggressive. The results of the match are shown in the B2 experiments of Fig. 5. The righteous side has a win rate higher than the MF-Q algorithm.
rate of 78%, winning 39 rounds, and surpassing the opponents. In the B3 experiments, the emotional state of both groups is negative. The righteous side is afraid of the opposite side, and the opponents tend to provoke and attack the righteous side. In this case, the opposite side can take advantage of the negative emotions of the opponent’s low morale to attack the righteous side. This will have a higher win rate. However, the win rate of both groups is 0.54 : 0.46, the winning number of the righteous side is slightly more. Since the opposite agent cannot perceive the emotions of itself and others, it cannot use the emotional advantage to plan favorable actions. When the righteous side is planning action, they can be combined with emotional information for comprehensive consideration. If the righteous side perceives that the opponent’s emotional state is negative and the combat state is aggressive, they will tend to adopt moving-type actions to avoid blind attacks and protect themselves from harm. Therefore, the opposite side has a low win rate.

We randomly select a round of battles from the B2 and B3 experiments, as shown in Figs. 6 and 7. The blue curve represents the righteous side and the red curve represents the opposite side. Fig. 6a is the mean emotional value of both groups at each step. The initial emotional state of both sides is positive. As the battle progresses, the emotions of the righteous side become more positive, and then remain in a positive state. The emotions of the opposite side firstly gradually become more negative and then gradually become positive. Fig. 6b is the remaining number of survivors on both sides at each step. At about step 200, as the emotions of the opposite gradually become more positive, the agent becomes more afraid of the righteous side, resulting in a large number of members are subdued by the righteous side. In Fig. 7a, the initial emotional state of the righteous side is negative. However, as the battle progresses, the emotions of the righteous side quickly become positive, and the action is adjusted in time based on the perceived emotional information, and eventually win. Fig. 7b shows that at the end of the battle, the number of survivors on the righteous side is significantly greater than that on the opposite side.

We use a new indicator to compare the three algorithms of ACSED, MF-Q, and ACSEE. This indicator is the ratio of the number of survivors on both sides, indicating the ratio of the number of survivors on both sides at the same time. In the experiments, we set the same experimental conditions, including the location of the agent, the number of people, the emotion, the size of the map, and so on. We ensure the consistency of the experimental conditions, and then use the three algorithms for the antagonistic crowd simulation and record the number of survivors in each algorithm at each time step. When setting the initial emotional value, considering that the main task of the righteous side in the riot scene is to pacify the riot, the righteous emotion is designed to be a more positive emotion, which tends to actively attack the other group. The overall quality of the righteous side is higher than the opposite side, and the will to subdue the enemy is stronger. Thus, we set the emotional value range of the righteous side is (0.7, 0.9), the emotional value range of the opposite side is (-0.8, 0.5). In the initial state, there are equal numbers on both sides.

We randomly select a round of battles, as shown in Fig. 8. According to the experimental results, the MF-Q algorithm has the fastest convergence speed, which is slightly faster than our algorithm. However, the MF-Q algorithm does not consider the emotion of the agent, and cannot perceive the emotional changes of the surrounding teammates and opponents. This will simplify the battle process to a certain degree, reduce the rationality of the simulation, thereby
speeding up the convergence process. In our results, the righteous side overwhelms more opponents with less cost. Under the same conditions, the righteous side fails in the ACSEE algorithm. Although the ACSEE algorithm considers the antagonistic emotions of the crowd, it does not consider the situation where the two sides face each other first and then battle. In the riot, not only the two sides battle directly, but also the two sides face each other first and then battle. The simulation scope of the ACSEE algorithm is more local. So in a round of random experiments, the righteous side fails. Under the indicator of the ratio of the number of survivors of righteous and opposite sides, the results of our algorithm are significantly higher than the other two algorithms. While ensuring that the crowd’s emotions are taken into account, in our algorithm, the righteous side can subdue the other side faster, and the ratio is increased from the initial 1 to 60, which shows that more opponents are subdued. More details can be seen in the supplementary video at https://lvpei.github.io/assets/Demo-TAC-ACSED.mp4.

Experiments have proved that by fully considering the emotions of both sides we can truly grasp the current battle situation, understand the opponent’s combat state and the actions taken. It proves the rationality and necessity of considering emotional factors when planning the action of both sides. In the event of a sudden riot, using the algorithm proposed in this paper provides help for the righteous side to formulate better uniform strategies.

4.1.3 Two Sides With Different Numbers of Agents

The experiment in this section discusses the influence of different numbers of people on combat results when the righteous and the opposite emotional states are both positive. According to Table 1, the positive emotion on both sides means that the righteous side is more aggressive than the opposite side. This section consists of two sets of experiments. In the first set of experiments, there are three comparative experiments, the number of combatants on the righteous side remains unchanged, and the number of the opposite side is changed. Both sides use the proposed algorithm in this paper to fight. The initial number is: 75 versus 75, 75 versus 90, 75 versus 100. Fig. 9 shows the result of the experiments. When the number of both sides is same, the righteous side wins. When the initial number of the opposite side is increased to 90, the righteous side still wins. When the number is increased to 100, the righteous side loses. Experiments show that the righteous side can win more with less when the two sides have positive emotions, but when the initial number of the two sides is quite different, the probability of winning will become less.

Table 4 is the result of the second set of experiments. The righteous side uses ACSED algorithm and the opposite side uses MF-Q algorithm. When the initial number of the righteous side is 256 and 192, the righteous side wins. When the initial number of the righteous side is reduced to 128, the righteous side loses the battle. The algorithm proposed in this paper can still win more with less when playing against the MF-Q algorithm, and the righteous side still can’t beat the opposite side when the initial number of people gap is large. Moreover, in these two experiments where the righteous side wins in Table 4, the win rate is generally higher than that of the righteous side in Table 3.

Experiments prove that the righteous side who has a positive emotional state in combat can increase the win rate to a certain extent. Subject to objective conditions, if there is a large difference in the number of people between the two sides in the battle, it cannot rely solely on the positive emotional state to win. In the face of real crowd confrontation incidents, the experimental conclusions in this section have some reference

| TABLE 3 | The Win Rate of Both Sides under Different Numbers of People Using the ACSED Algorithm |
|---------|--------------------------------------------------|
| Initial number of both groups | Win rate |
| 75 : 75 | 0.72 : 0.28 |
| 75 : 90 | 0.58 : 0.36 |
| 75 : 100 | 0.38 : 0.62 |

| TABLE 4 | The Winning Rate of Both Sides With Different Numbers of People Using Different Algorithms |
|---------|--------------------------------------------------|
| Initial number of both groups | Win rate |
| 256 : 256 | 0.78 : 0.2 |
| 192 : 256 | 0.62 : 0.38 |
| 128 : 256 | 0.34 : 0.62 |
value for formulating actual combat plans. When formulating plans, it is necessary to combine emotions and reasonably arrange the number of participants in combat.

4.2 Comparison of Simulation Results With Real Scenes

In this section, we use the proposed algorithm to simulate real confrontation cases, and verify the authenticity and practicability of the simulation results through crowd movement trends and position distribution. Besides, we compare our algorithm simulation result with the MF-Q algorithm and the ACSEE algorithm. The main goal of our algorithm is to predict the movement trend of the crowd, and under certain mission constraints, formulate better combat strategies. The results show that our algorithm can obtain simulation results that are the closest to real video.

Fig. 10a shows a real riot. The purpose of the police is to control the riots provoked by the lawless, and to subdue them to maintain social order. In the video of the real riot scene, the police have two main tasks, including subduing the lawless and preventing them from passing through the gate in the image. First of all, under the condition of constant provocation by the lawless, the police take the initiative to attack the lawless. The lawless constantly move and retreat. Then, after the police rush out a distance, they retreat to defend the gate in order to carry out the second task. Finally, the lawless see the police retreat, and immediately rush to the police to attack, so that the two sides fight. In order to make our simulation results more realistic and reasonable, only local control is flawed, so global control is also added. Therefore, the task of the police is abstracted into global control, with rewards for subduing the lawless and defending gates. It is necessary to change the parameter setting of the reward. Suppose the gate is a region in the grid world. If the distance between the righteous member and this area is greater than a certain threshold, it will be punished at the current time step. Obviously, the righteous side retreats after the attack in the real video. Therefore, we add the rule that when the opposite side retreats in a large

Fig. 10. Comparisons between real scenes and our simulation results. (a) is a real crowd antagonistic scene. (b) is our corresponding simulation results. The yellow cylinder represents the group wearing black who is the opposite crowd, and the blue cylinder represents the group wearing black clothes who is police. (c) is a real confrontation exercise scene. (d) is our corresponding simulation results. The white cylinder represents the group wearing white clothes, and the blue cylinder represents the group wearing dark clothes.
scale, the righteous side also retreat to defend the gate. The final simulation results are shown in Fig. 10b. More details can be seen in the supplementary video.

Fig. 10c shows a real confrontation exercise scene. The group wearing white clothes represents the righteous side, and the group wearing black clothes represents the opposite side. At first the opposite side attacks the righteous side, and then they begin to battle. The two sides are evenly matched in numbers and the behavior of the opposite side is still under control, so the righteous side chooses not to take the initiative to attack. This requires the addition of global control. The righteous side must obey the overall combat strategy and cannot rush to the opponent just because of aggressive emotional state. Therefore, we add global control as a rule to limit the actions of the righteous side. When the distance between the two sides is lower than a certain threshold and the emotional state of the opposite side is very aggressive, the righteous side will start to attack. Fig. 10d shows a simulated scene. Details are in the supplementary video.

We quantitatively evaluate the simulation results using dominant path, entropy metric and angular error as [45]. The dominant path is defined based on the collectiveness of the movement of the crowd. Collectiveness describes the extent to which individuals act as a unit in collective movements and is a fundamental and pervasive measure of various crowd systems, including crowds in confrontation scenarios. We calculate collectiveness using the method in [58]. A group is formed when the collectiveness of the agents in a certain area is significantly higher than that of the surrounding area. The center of this group is determined from the average of the positions of all agents in the group. The trajectory at the center of the group forms the dominant path. We use this method to calculate the dominant path of the real-world video and our simulation results. We then evaluate our crowd simulation results using entropy metric and angular error. They are used to evaluate the error of the trajectory and movement direction, respectively.

The entropy metric is employed to evaluate the error between the dominant path of the simulation results and that of the real-world video. The lower the entropy value, the higher the similarity. It can be seen from the Table 5 that our algorithm has the lowest entropy value and is closest to the dominant path of the real video. We also use the angular error between the movement direction in the simulation results and that in the real video as an evaluation metric. Angular error is defined in Formula (16). $V_x$ and $V_y$ is the movement direction of the real-world video.

$$AE = \cos^{-1}\left( \frac{(V_x \cdot V_{x_{gt}} + V_y \cdot V_{y_{gt}})}{\sqrt{V_x^2 + V_y^2} \sqrt{V_{x_{gt}}^2 + V_{y_{gt}}^2}} \right)$$

(16)

A lower entropy value means a higher similarity between simulation results and real-world scenarios. Simulations with entropy value less than 1.0 are considered visually very similar to the source data, while those with value greater than 6.0 are visually very different. A lower value of angular error means a higher similarity to real-world crowd videos. We report the mean and variance of angular error at different time steps. Table 5 shows that our algorithm consistently outperforms the MF-Q algorithm and the ACSEE algorithm. Compared with the MF-Q algorithm, our algorithm takes into account the influence of emotions on the agent and can formulate a combat strategy with a higher win rate. Compared with the ACSEE algorithm considering the evolutionary game theory, we use deep reinforcement learning to predict antagonistic behavior, and the simulation results obtained are more reasonable.

By comparing the real scene and the simulation one, we can see that the movement trend of the crowd in the simulation is basically the same as that in the real scene. This shows that our algorithm is in line with reality and can simulate crowd confrontation incidents well.

5 Conclusion

This paper proposes an emotional contagion-aware deep reinforcement learning model for antagonistic crowd simulation. We build an antagonistic emotional contagion module based on the SIS epidemic model and the reward value obtained by the agent according to the combat situation. When modeling crowd behaviors, the deep reinforcement learning technology is used to predict the action of the agent. The DQN and mean field theory are introduced to predict the action in the crowd. In addition, our model considers the specific influence of emotions on antagonistic crowd behaviors. We determine the individual combat state through the emotional value, and re-plan more reasonable actions for the agent according to the behavior rules. The model proposed in this paper is proved through a variety of experiments. For one thing, it can simulate the antagonistic crowd behaviors more realistically and help to study crowd movement trend under riots. For another, it can provide a reference for the formulation of combat plans, thereby improving the win rate.

Although our work can contribute to the control and calming of emergencies, there are still some shortcomings. In real world, groups that provoke riots are often very irrational and extreme, they are more uncontrollable than normal groups. The simulation result of our model may only be one case of many real situations, and they may not completely follow the result calculated by our model. In future work, we will continue to improve our prediction results considering more actual situations of antagonistic crowds. Furthermore, we cannot directly obtain or accurately infer the emotions in crowd antagonistic scenes. The videos are generally captured by passers-by at the riot scene, and they will shake the video and cause the picture to be chaotic because of their fear and
nervousness. Most of the videos are of low quality. Therefore, the initial emotional state of our model is empirically set from real-world videos, which is not very accurate. In the future, we plan to use the latest wearable devices to collect this data, providing an efficient way to obtain the initial state of our model more efficiently and accurately.

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