An Emotion Evolution based Model for Collective Behavior Simulation

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ABSTRACT

Current crowd simulation progresses still fall short of simulating many real-world collective behaviors. Arguably, one of the main reasons is that some essential qualities of human beings such as emotion have not been effectively modeled and incorporated into crowd simulation algorithms. In this paper, we propose a novel computational model for emotion evolution and demonstrate its applications for crowd simulation. Specifically, our approach is designed to tackle three major issues in the emotion evolution process: (i) how to perceive and evaluate emotion when individuals face emergency or external events, (ii) how to evolve the emotion during induction, and (iii) how specific actions of individuals in a crowd are impacted by emotion. Through many experiments, we demonstrate that our method can effectively simulate emergent dynamic collective patterns observed in real-world crowd footages.

CCS CONCEPTS

• **Computing methodologies → Agent / discrete models**; **Procedural animation**;

KEYWORDS

Crowd simulation, emotion evolution, social psychology, and collective behavior

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1 INTRODUCTION

Collective behavior is the spontaneous and unstructured movement of a group of people when facing and responding to the same event, stimulus, or influence. In particular, at certain scenarios collective behaviors could turn into striking mass incidents (e.g., riots, mobs, or panic evacuation) [Xu et al. 2014]. Therefore, modeling and simulating collective behaviors under various scenarios is of significant importance to many 3D and virtual reality applications, including but not limited to entertainment, public safety, urban planning, and emergency training. In the real-world, individuals in a crowd constantly adjust their psychological and affective states according to the dynamic change of environment. So, the collective behavior forming process is highly dynamic and unstructured, which imposes significant challenges to realistically simulate such behaviors.

Previously numerous works have been developed by introducing physical mechanics and dynamics into crowd simulation, including the well-known social force model [Helbing et al. 2000], synthetic vision based model [Ondřej et al. 2010], and hierarchical crowd simulation structure [Musse and Thalmann 2001]. Later, the concept of fluid dynamics have been introduced to characterize pedestrian flows at macroscopic level [Narain et al. 2009; Treuille et al. 2006]. Furthermore, velocity obstacles in robotics field was also introduced into multi-agent navigation for simulating large-scale crowds [Guy et al. 2009; Jur et al. 2008].

Sociological and psychological factors have also been exploited to simulate realistic collective behaviors. For example, social cognition behaviors and personality model have been introduced to simulate heterogeneous crowd behavior [Durupinar et al. 2011; Guy et al. 2011; Kim et al. 2012; Pelechano and Badler 2006]. All these methods employ fixed personality traits or response patterns for individuals, without modeling the dynamic evolution of emotion of individuals in a crowd.

Since "collective behavior" was originally coined by Robert E. Park [1921], many theories on collective behaviors have been proposed including the well-known emergent-norm theory [Turner and Killian. 1993]. These theories emphasize that *emotion* plays a vital role in forming collective behaviors. The early modern psychology theory [Wundt 2010] assumes emotion is composed of three dimensions. Several dimensional models of emotion have been widely used in virtual agent modeling, including the two-dimensional model of emotion (intensity and duration) [Le et al.

2010], the OCC model and its variations [Durupinar et al. 2016; Ortony et al. 1990], and the OCEAN model [Durupinar et al. 2011] that simulates emotional mobs through the combination of psychological components.

In this paper, we draw insights from existing social psychology and biological immune system studies to simulate how individuals in a crowd deal with the dynamic changes of external environment. Our main contribution is the modeling of *emotion evolution* in a crowd and its influence on collective dynamic behaviors. Different from assigning individuals with fixed personality traits or response patterns as in previous methods (e.g., [Durupinar et al. 2011; Guy et al. 2011; Kim et al. 2012]), the key rationale of our method is, individual-specific emotion evolution drives the dynamic behaviors and responses of individuals in a crowd. In our approach, we employ Wundt's three-dimensional emotion model [Wundt 2010] and our approach is focused on modeling the evolution of emotion, while all the existing works have not considered and modeled it for crowd simulation.

2 OUR METHOD

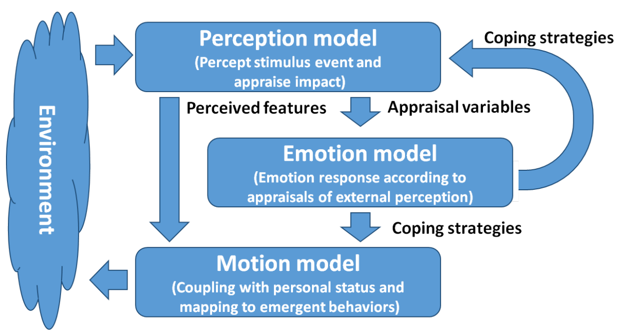


Figure 1: The schematic illustration of our PEM (Perception, Emotion, and Motion) model.

Our method is called the *Perception*, *Emotion* and *Motion* (PEM) model, consisting of three main sub-models as described below. Figure 1 illustrates the schematic view of our PEM model.

Perception Model: Individuals can perceive various induced events in the environment, from simple accidents to complex social situation transforms (e.g., explosion, fire, and reaction of other individuals). Conceptually, the perception model establishes a bridge between the external world and the internal states of individuals.

Emotion Model: By perceiving and appraising the events in the environment, individuals' emotions can be dynamically influenced. This influence process takes both the perceived external events and the internal states of the individuals into consideration. The emotion evolution model introduced in this work is designed to model the self-evolution of individuals' emotions, as well as the emotion inter-play among individuals.

Motion Model: The evolved emotion can take effect on the movements of individuals, represented as the changes of orientation, speed, position, etc. Meanwhile, individuals can adapt to the dynamically changing, external environment through the continuous adjustment of their movements. In our approach, via a physically-based crowd simulation model we can realistically simulate collective reaction behaviors under the influence of the evolved emotion.

2.1 Perception Model

The cognitive theory of emotion states that emotion is produced by evaluation of stimulation or events [Scherer et al. 2001]. Specifically, it can be interpreted as follows: stimulation is not the direct cause of emotion experience; however, the stimulation needs to be evaluated before the arousal of emotion.

First, we need to map an external stimulus into a quantized value to describe an agent's sensing on it. Specifically, we calculate the average perceived intensity of an agent with respect to a particular stimulus using the following intensity mapping function:

$$F = \sum_{0}^{T} \frac{M_s}{4\pi(\Delta P)^2}\Delta t. \tag{1}$$

Here F denotes the radiation perceived by an agent, M_s denotes the physical intensity corresponding to the source of the stimulus such as the sound intensity, ΔP denotes the relative position from an agent to the stimulus source, T denotes the time period which the stimulus M_s is applied, Δt denotes the time step. Suppose that the stimulus is radiated outward from a point source in a three-dimensional space. According to the inverse-square law in physics, a specified physical intensity is inversely proportional to the square of the distance from the source of that physical intensity to an agent.

As an example of F, the sensed acoustic intensity is attenuated with the increase of the relative distance. Therefore, we can adapt different stimuli or events to the intensity mapping function by defining different source intensity M_s, such as thermal radiation, explosion, or other agents' negative emotions.

Then, we further transform the calculated intensity of the stimulus to the internal state of an agent. Despite the variety of stimuli in the environment, Stevens reported that the psychological volume arises in a direct proportion to a power function of the stimulation volume [Stevens 1957]. According to the power law, we use the following function to transform the stimulation intensity to the strength of psychological induction of an agent.

$$S = \begin{cases} b(F - F_0)^{\alpha}, & F > F_0 \\ 0, & F \le F_0 \end{cases} \tag{2}$$

Where S denotes the perceived psychological volume of an agent, F denotes the calculated stimulation intensity, F_0 denotes a user-defined threshold, α denotes a power exponent that depends on the type of stimulation, and b denotes a proportionality constant determining the scale unit. In our simulation, we take $b = 1.2$ and $\alpha = 0.33$ under normal circumstances. These parameters will be adjusted with reference to the relevant research results in psychology literature.

2.2 Emotion Model

In emotional activities, people not only accept the impact of external events, but also regulate themselves to respond to the stimulation. Emotion is caused by the evaluation to the stimulus event and the feedback of the physical action. In this work, emotion evolution mainly focuses on how to define the emotional dimension of an agent and the dynamic evolution process.

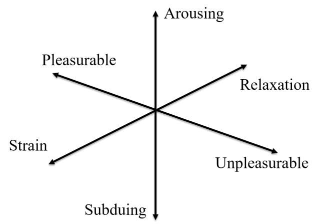


Figure 2: Three dimensions of the used emotion model

The Wundt's emotion model [Wundt 2010] has three dimensions: happy or not, excited or not, and nervous or not. Each specific sentiment is distributed in different position of three dimensions between the two poles. As illustrated in Figure 2, we define a three-dimensional emotion space E <p=pleasurable or unpleasurable, r=arousing or subduing, a=strain or relaxation>, where the range of each dimension is $[-1, 1]$:

$$E = \begin{bmatrix} e_p \\ e_r \\ e_a \end{bmatrix} \tag{3}$$

Therefore, we can define a three-dimensional psychological volume I, which is computed by summing up individual psychological volumes caused by different external stimuli, described below.

$$I = \begin{bmatrix} I_p \\ I_r \\ I_a \end{bmatrix} = \begin{bmatrix} \sum k_{pi}\omega_{pi}S_i \\ \sum k_{ri}\omega_{ri}S_i \\ \sum k_{ai}\omega_{ai}S_i \end{bmatrix} \tag{4}$$

where $\omega_{pi} + \omega_{ri} + \omega_{ai} = 1$, and $k_{pi}, k_{ri}, k_{ai} \in \{1, -1, 0\}$ denote emotion coefficients, since we assume emotion fluctuation can be positive, negative, or neutral under the influence of an external stimulus.

On top of the above definitions, we model the evolution of individuals' emotions. Inspired by the immune feedback system for tracking control of a flexible micro-actuator [Kawafuku et al. 1999], we introduce an emotional evolution model based on a similar immune feedback mechanism.

Emotion reactivity is similar to the nature immune system. Specifically, first, both the immune system and emotion reactivity are responses to external stimuli; second, they are similar in terms of their reaction process. In the biological immune system, T-cells play a key role in immune response; Helper T-cell can activate and Suppressor T-cell can inhibit the level of immune response for foreign antigens. The human body also can adjust the secretion of the brain's monoamine neurotransmitters through the perception of external stimuli. Different monoamine neurotransmitters can facilitate or inhibit the body's emotion and then ultimately regulate individual behavior; that is to say, depending on whether the response achieves individual's expectation, it will excite or inhibit emotions and then drive individual to deal with external stimulus.

Thus, inspired by the above immune feedback mechanism, we design an emotional evolution model. Specifically, an agent's emotion is represented by the aforementioned three-dimensional Wundt's

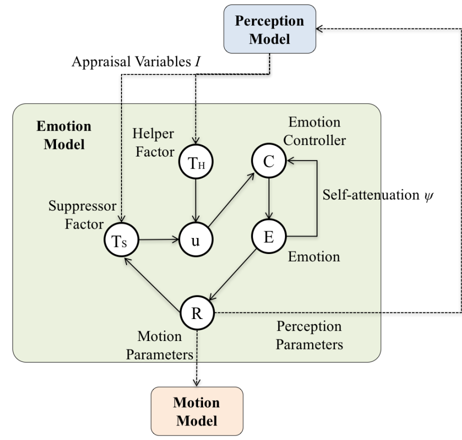


Figure 3: The proposed emotion evolution model

emotion model, and emotional evolution is described by a similar immune feedback mechanism, as illustrated in Figure 3. When an external event occurs, the human's sensory organs are stimulated. The stimulus is then transformed to an individual's psychological volume I, which further adjusts emotion through an emotion controller c in our model. This controller contains the following three parts: (i) a helper factor T_H: an individual's psychological volume directly excites the fluctuation of emotion through T_H; (ii) a suppressor factor T_S: individuals gradually adjust their emotions to adapt to the external environment, and ultimately the emotions will be gradually suppressed to maintain a proper balance; (iii) a self-attenuation factor Ψ: Emotion will return gradually to the neutral state after all external stimuli disappear.

Therefore, the emotion controller c can be defined as follows:

$$\Delta c = T_H - T_S - \Psi \tag{5}$$

$$T_H = k_1 I \tag{6}$$

$$T_S = k_2 h(\Delta R) I \tag{7}$$

where k_1 and k_2 are weighting factors for T_H and T_S, respectively; $h(\Delta R)$ is a function introduced to describe an individual's adaptability to the environment (i.e., suppress emotional fluctuations). We define $h(\Delta R)$ as follows.

$$h(\Delta R) = \sum_i \xi_i \frac{|R_i(t-d) - R_i(0)|}{\tau_i} \tag{8}$$

where ΔR denotes the difference between the behavior parameters at time $(t-d)$ and the original parameters, five-dimensional variable R is described by Equation 13, τ_i is the normalizing factor, which equals to the maximum value of parameter i, and the weighting vector ξ_i is empirically set to $[0.1, 0.1, 0.2, 0.3, 0.3]$. Interacting with two primary feedback mechanisms, including the activation mechanism T_H and the inhibition mechanism T_S, an individual can respond to external environmental stimuli very quickly.

Emotion has the characteristic of self-attenuation. In this work, we approximate the decaying curve of emotion as an exponential curve [Marreiros et al. 2010] and the function is defined as follows:

$$\Psi = e_t \exp\left(-\lambda \Delta t\right) \tag{9}$$

where e_t denotes the current emotion at time t, λ denotes the decaying rate, which is set to 3.0 in our experiments, and Δt denotes the time step.

If we further simplify the formula Δc in Equation 5, we can have:

$$\begin{aligned} \mathrm{u} = &\ T_H - T_S \\ &= k_1 I - k_2 h\left(\Delta R\right) I \\ &= K\left(1 - \eta h\left(\Delta R\right)\right) I \\ &= \ K_p I \end{aligned} \tag{10}$$

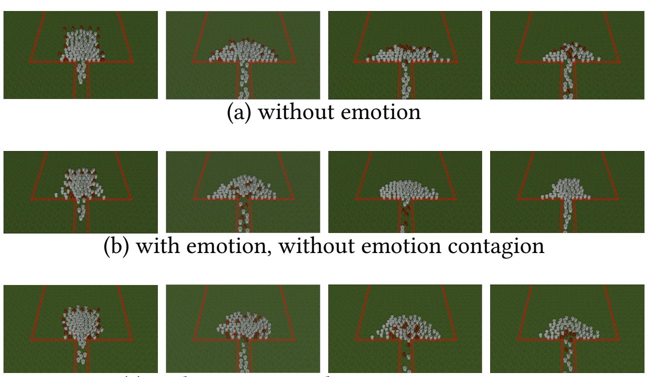
where $\mathrm{K} = k_1$ and $\eta = k_2/k_1$, taking $\mathrm{K} = 0.8$ and $\eta = 0.1$.

The emotion controller c can be simplify described as a combination of external stimuli and self-attenuation.

$$\Delta \mathrm{c} = \mathrm{u} + \Psi = K_p I + \Psi \tag{11}$$

Finally, the mathematical expression of one dimension of an individual's emotion (refer to Equation 12), e, can be described as follows:

$$e_{t+1} = \begin{cases} 1, & e_t + \Delta c > 1 \\ e_t + \Delta c, & -1 \leq e_t + \Delta c \leq 1 \\ -1, & e_t + \Delta c < -1 \end{cases} \tag{12}$$



(a) without emotion

(b) with emotion, without emotion contagion

(c) with emotion, with emotion contagion

Figure 4: Snapshots of our simulation experiments for validating the "more haste less speed" phenomenon

2.3 Motion Model

Under normal situations, individual behaviors in a crowd are impacted by their own conscious emotions, and they typically are not impetuous or excited. However, when people are stimulated by external events such as emergency, they could become irritable and unbounded. For example, when earthquake comes, people will typically attempt to escape to any open space from the current location as soon as possible. Their actions are often fast and radical. These collective behaviors will inevitably lead to a stampede all of a sudden.

Emotional impact on human behavior needs to be reflected on the physical movement of the crowd at the end. Therefore, we define a transfer matrix for behavior parameters, and different emotions will be reflected through different behavior parameters. In this work, five behavior parameters are affected by emotion, including neighbor distance, max neighbors, planning time horizon, agent radius, and max speed. Therefore, a five-dimensional variable R that contains these behavior parameters is defined as follows:

$$R = \begin{bmatrix} r_{neighbordist} \\ r_{maxneighbors} \\ r_{timehorizon} \\ r_{radius} \\ r_{maxspeed} \end{bmatrix} \tag{13}$$

The transfer relationship between emotion and behavior parameters is established as follows:

$$R_{t+1} = A * E + R_t, \tag{14}$$

where

$$A = \begin{bmatrix} -5.03 & 5.14 & -5.16 \\ -5.4 & 5.58 & 5.84 \\ -5.22 & 5.31 & 5.32 \\ 0.15 & -0.28 & -0.36 \\ 0.49 & -0.21 & -0.57 \end{bmatrix}$$

denotes a 5×3 empirically-defined, transfer matrix containing the impact factors of different parameters, E denotes a three-dimensional emotion space (refer to Equation 12), and R_t denotes an agent's motion parameters at time t. We calculate each agent's emotion before the simulation at each step, and then we use it to update the agent's behavior parameters.

2.4 Simulation

Based on the above layered architecture, we can straightforwardly incorporate our hierarchical emotion evolution model to existing agent-based models [Helbing et al. 2000; Reynolds 1987; RVO2 2017]. In this work, we choose the RVO model [RVO2 2017] for our experiments due to its high efficiency for real-time multi-agent navigation. Also, in the RVO model, each agent navigates independently without explicit communication with other agents. It can guarantee safe and oscillation-free motions for each agent.

3 EXPERIMENT RESULTS

To test our model, we have conducted various simulation experiments and comparisons, detailed in this section. The configuration of the experimental computer in all of our experiments is: Intel(R) Xeon(R) E5-1620, and 8GB memory. For the animation results of all our experiments, please refer to the accompanying demo video.

3.1 Emotional Contagion Experiments

In order to test the effects of emotion and emotional contagion on pedestrian dynamics by our method, we built a classic evacuation scene as shown in Figure 4. With the same scene, we conducted three simulations with different social psychological settings: (a) without emotion; (b) with emotion, without emotion contagion; and

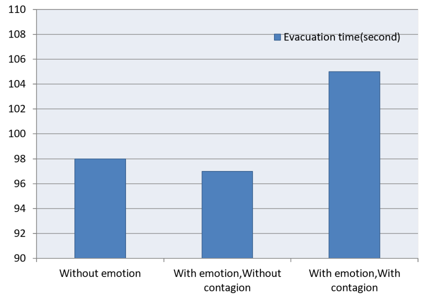
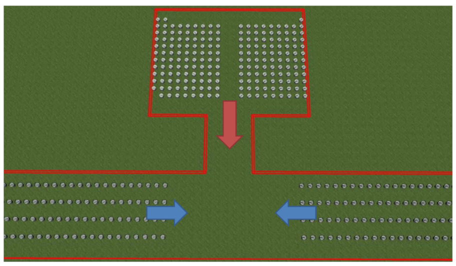
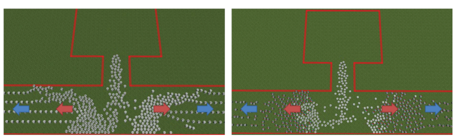


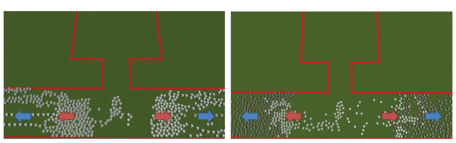
Figure 5: Evacuation times of three different conditions



(a) The initial stage



(b) An intermediate stage



(c) The final stage

Figure 6: Comparisons between the SFM model (left) and our model (right)

(c) with emotion, with emotion contagion. The essential difference among the three experiments are: (i) whether those red agents in Figure 4 are emotional, and (ii) whether emotion is contagious among the agents.

As shown in Figure 4 (also refer to the accompanying demo video), those emotional (red) agents can evacuate quickly by jostling or pushing other agents. However, as shown in Figure 4(c), they arouse the tension emotion of most of the other agents; as a result, most of the agents in the scene jostle each other for better positions. At the end, the experiment with both emotion and emotion contagion (Figure 4(c)) took the longest evacuation time, as illustrated in Figure 5. The experiment without emotion (Figure 4(a)) needs slightly more time than the experiment with emotion but without emotion contagion (Figure 4(b)), because all the agents (include those emotional agents) in Figure 4(a) move in their normal paces since they are not affected by any emotion. By contrast, the experiment with emotion but without emotion contagion (Figure 4(b)) took the least time, although other agents (except those emotional agents) in Figure 4(b) still move in their normal paces since they are not affected at all by the emotional agents, but the emotional agents can compete with other individuals for better positions (Figure 4(b)). This suggests that a certain level of jostling or pushing by some agents could help to reduce the total evacuation time. In the experiments, stimulated crowds lead to a classic disorder evacuation scene, and their evacuation time would be substantially longer than normal cases, where all the agents move in their regular paces without panic emotion.

3.2 Comparison with SFM-based Evacuation

We also compared our model with the well-known Social Forces Model (SFM) for panic evacuation. In the SFM model, its original authors present a panic model and simulate a test scene in which pedestrians attempt to leave a smoky room with only one exit [Helbing et al. 2000]. Each individual has to follow a mixture of his/her intended direction and the average direction of its neighbors within a certain radius. We tested the same evacuation scene (i.e., a similar smoky room) using both our model and the original SFM model, and the comparison results are shown in Figure 6 as well as the accompanying demo video. From the comparison results, we can see that our model can produce more natural collective behaviors than the SFM model due to its simulation of emotion spreading.

3.3 Comparisons with Real-world Evacuations

We also tested the effectiveness of our model by comparing its simulation results with some video footages of real-world crowds. We selected four real-world video footages to cover three typical group behaviors in real world, including expressive crowds, casual crowds, and acting crowds, detailed below. It should be noted that such comparisons are very challenging, since it is infeasible for us to accurately reproduce the actual 3D environments in the video footages, and it is also difficult to determine the exact number of people and their locations in the scene. However, as described below, our method can reasonably simulate and characterize the group behaviors of different categories of crowds in the selected video footages (refer to the accompanying demo video).

The 1st row of Figure 7 shows the experiment result of an expressive crowd. In this scenario, a big crowd of fans and other people are in the arrival gate of an airport. When the celebrity comes out, the fans surround the celebrity immediately. We built a similar scene to simulate this crowd. We can see that the agents automatically form a dynamic circle-like shape, and the formed circle of agents is jammed inside but loose on the periphery just like what is shown in the video footage.

The 2nd row of Figure 7 shows the simulation result of a casual crowd. Specifically, a passenger's cell-phone was flaming in a subway train, and this makes passengers fermented, trying to escape from the train as soon as possible. People close to the passenger with the flaming cell phone are the first group who attempt to escape from the train and others follow on. From our simulation result, we can see that our model is able to effectively simulate such an emergency evacuation effect.

The 3rd row of Figure 7 shows the simulation result of an acting crowd. In this crowd, police are at one side of the scene to form a human wall in order to disperse demonstrators. When the polices are gradually approaching the demonstrators, strain are placed on the latter and the latter start to retreat. In addition, when the polices throw smoke bombs into the demonstrators, a new stimulus event occurs. From this point, the demonstrators are subject to multiple stimuli; they have to further accelerate the escaping under terrible strain. In our simulation result, the demonstrator agents start to escape from the scene when police agents are approaching them. When an additional stimulating event such as the explosion of a smoke bomb happens, the demonstrator agents speed up the escaping from the scene, which is in line with what happened in the video footage.

The 4th row of Figure 7 shows the simulation result of a second acting crowd. In this crowd, a large number of subway passengers jam in the door, waiting for the arrival of the subway. Because the outside passengers block the door and want to enter the compartment as soon as possible, passengers within the subway need to forcefully squeeze out the door when the subway arrived. From our simulation result, we can see that our model can soundly reproduce the very congested scene.

Figure 7: Comparisons between real-world video footages and simulation results by our approach: an expressive crowd (1st row), an casual crowd (2nd row), an acting crowd (3rd row), and a second actin crowd (4th row). The left most panel in each row shows a screenshot of the recorded video footage.

4 DISCUSSION AND CONCLUSION

In this paper we present a novel model for simulating crowd behaviors when facing external stimuli based on the core idea of emotion evolution. In particular, our method focuses on the modeling of emotion evolution with the context of a crowd and its influence on group behaviors. We have conducted a variety of simulation experiments as well as comparisons, and we show that our approach can effectively simulate emergent dynamic collective patterns, including challenging comparisons with real-world crowd video footages.

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