Research on Prediction Methods of Prevalence Perception under Information Exposure

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Abstract: With the rapid development of information technology, the explosive growth of data information has become a common challenge and opportunity. Social network services represented by WeChat, Weibo and Twitter, drive a large amount of information due to the continuous spread, evolution and emergence of users through these platforms. The dynamic modeling, analysis, and network information prediction, has very important research and application value, and plays a very important role in the discovery of popular events, personalized information recommendation, and early warning of bad information. For these reasons, this paper proposes an adaptive prediction algorithm for network information transmission. A popularity prediction algorithm is designed to control the transmission trend based on the gray Verhulst model to analyze the law of development and capture popular trends. Experimental simulations show that the proposed perceptual prediction model in this paper has a better fitting effect than the existing models.

Keywords: Social network, situational awareness, adaptive prediction, prediction of popularity.

1 Introduction

The rapid development of online social networks has led to an explosive growth of information. However, the perception and prediction of information transmission is difficult in this field of research. Network information transmission prediction is generally divided into macro prediction and micro prediction. The macro prediction

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Received: 10 February 2020; Accepted: 29 May 2020.

method starts from the overall information transmission and predicts the future situation, breadth, number of audiences, speed, and depth of the information transmission [Cui, Song and Miao (2017)]. The micro prediction starts from the user node and predicts whether an individual user will spread certain information. Most researches of information transmission prediction methods are mainly based on the information transmission data that has occurred, on analyzing the influencing factors of information transmission and on predicting the state of future information transmission based on the observed actual data. Yang et al. [Yang, Guo and Cai (2010)] have found that a factor graph model is proper to predict the depth of information transmission. This model uses multiple factors, such as user relationships and network structure. However, the factor graph model does not introduce a time factor, so it cannot predict the speed of information transmission. Yang et al. [Yang and Counts (2010)] have found that the research on the prediction of transmission depth, breadth, and transmission speed in the process of information transmission uses feature selection methods and attenuation models to predict it. The characteristics used in it mainly include the user's social attributes and information forwarding attributes. The study found that the number of "@" and the timing characteristics of reposting are critical to the accuracy of the information transmission depth, breadth, and transmission speed prediction.

While social networks attract users to participate, the related popularity predictions have also attracted the attention of a large number of scholars. According to the time of prediction, the research on the prediction of popularity can be roughly divided into two categories: pre-content and post-content prediction [Xiao, Liu and Li (2018); Liu, Yang and Liu (2018)]. Pre-content predictions have large deviations in the popularity distribution, and it is difficult to predict accurate value directly. In recent years, many models and methods have emerged for the popularity prediction problem, which can be divided into several groups based on the group, classification and time series [Ghosh and Shekar (2017)]. (1) The method based on the group state is to divide the nodes in the social network into several states. By simulating the group state transition process, an information transmission model is established to analyze the evolution trend of popularity. Wang et al. [Wang, Li and Feng (2013)] have found that much similarity between the spread of Weibo information and the SIS model, so the SIS model is used to predict Weibo's forwarding behavior. The experimental results show that the prediction error rate is very low. (2) The method based on the classification model uses machine learning methods to assign a weight to different influencing factors, and the popularity classification model is trained. A similar phenomenon was found in microblog information. The characteristics of forwarding users and the interaction between forwarding users and fans were extracted [Liu, Zhao and Xiao (2018)]. Through time slice processing, the classification model was used to predict whether the fans of forwarding users would participate in the topic at the next moment to perceive the spreading trend of information. (3) The prediction based on time series modeling mainly focuses on the time series corresponding to the process of user-generated content transmission. Then, the model is used to predict the popularity of user-generated content. Hu et al. [Hu and Hu (2016)] have found that the time series of popular topic popularity in short-term outbreaks, these sequences are highly similar, and then define the time series feature space of popularity, that is, the average value, trend, and period of popularity to analyze the change of popularity with time. The length of the minimum observation period is given to make a timely prediction. Tan et al. [Tan, Wang and Zhang (2016)] have found that a new popularity prediction time series model based on the popularity of online videos based on time series, which predicts based on the correlation between the variance of the cumulative view of the video. This model is superior to several existing popularity prediction models, but the disadvantage is that it does not consider the influence of external factors.

Based on the basic idea of network information transmission, this paper improves the self-chaos methods and combines adaptive adjustment strategies to construct an adaptive prediction model for situation awareness of information transmission. It predicts and analyzes the development law of information transmission. The adaptive prediction model has better prediction results. At the same time, this paper combines the gray system theory algorithm to serialize the current transmission information to form the initial data sequence; Then builds the accumulated generating operation and the mean accumulated generating operation based on the initial data sequence, and then estimates the parameters and predicts the popularity of the next moment of information based on the gray theory model, three evaluation indexes are also proposed to evaluate the algorithm. Experiments on the Sina Weibo dataset show that the proposed method performs better in predicting the popularity of network information.

2 Adaptive prediction of information transmission

2.1 Basic idea of situation awareness of information transmission

Situational awareness is a comprehensive understanding of environmental factors, predicting the state in the future to achieve a reasonable decision-making process [Huang, Zhou and Yang (2015); Jiang, Wang, Jiang et al. (2019)]. The basic idea of situational awareness of information transmission can be expressed as shown in Fig. 1.

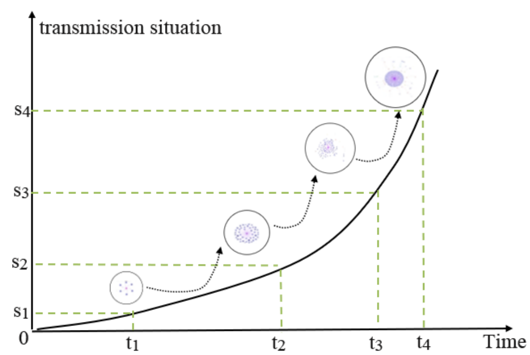

Figure 1: Basic idea of situation awareness of information transmission

It can be seen from Fig. 1, as time goes on, the trend of information transmission is also changing. At the time of t_1, the message has only six forwarding nodes; However, with the continuous attention of the social network users, the information has formed a certain scale of forwarding nodes at the time of t_2, but the overall situation of the information transmission is still in ripple and does not have some characteristics of the information explosion; The information transmission at the time of t_4 can be predicted by the values of s_1, s_2, and s_3 [Wang, Jiang and Qian (2014); Zhang, Guo, Shen et al. (2016)].

2.2 Adaptive prediction

Suppose the chaos time series of information is $\{x(t), t = 1, 2, \cdots n+T\}$, $x(t_1)$ to $x(t_n)$ are information transmission datas, we mainly predict the future transmission situation values of $x(t_{n+1})$, ..., $x(t_{n+T})$ (T is the prediction step). We set the length of a sliding window as m, from $x(t_{n-m})$ to $x(t_{n-1})$ find two points $x(t_n')$ and $x(t_n'')$ that are closest to $x(t_n)$, here not only the distance between $x(t_n')$ to $x(t_n)$ and $x(t_n'')$ to $x(t_n)$ are the smallest, and the distance between $x(t_{n-1}')$ to $x(t_{n-1})$ and $x(t_{n-1}'')$ to $x(t_{n-1})$ are also the smallest [Gao, Sun and Yang (2014)]. The two points have similar trends. So the values are also likely to be closer. The solution to the minimum distance is as follows:

Phase sequence reconstruction of the sequence:

$$\begin{matrix} x(1) & x(2) & \cdots & x(n) \\ 0 & x(1) & \cdots & x(n-1) \end{matrix}$$

Where time delay τ=1 and dimension m=2, Then find the minimum of $\left\| x(t_n) - x(t_{n-1}^{''}) \right\|_2$ and $\left\| x(t_n) - x(t_{n-1}^{''}) \right\|_2$.

Give $x(t'+1)$ and $x(t''+1)$ their corresponding weights ω_1' and ω_2'', the predicted value can be calculated by Eq. (1):

$$g(x(t_{n+1})) = w_1^{'} * (x(t_n^{'}) + 1) + w_2^{'} * (x(t_n^{''}) + 1) \tag{1}$$

The difference between the predicted value and the actual value at t_{n+1} is:

$$e(1) = x(t_{n+1}) - g(x(t_{n+1})) \tag{2}$$

At t_{n+2}, The weight value is calculated by Eqs. (3) and (4):

$$w_2^{'} = w_1^{'} + 2 * \mu * e(1) * \mathrm{x}(\mathrm{t}_n^{'} + 1) \tag{3}$$

$$w_2^{''} = w_1^{''} + 2 * \mu * e(1) * \mathrm{x}(\mathrm{t}_n^{''} + 1) \tag{4}$$

μ is the coefficient of control algorithm convergence.

Then the algorithm of the adaptive prediction model predicts the transmission situation of $x(t_{n+1})$, ..., $x(t_{n+T})$ can be expressed as the following recursive equation:

$$g\left(x\left(t_{n+p}\right)\right) = w_p^{'} * x\left(t_{n+p-1}^{'} + 1\right) + w_p^{''} * x\left(t_{n+p-1}^{''} + 1\right) \tag{5}$$

$$e(p) = x\left(t_{n+p}\right) - g\left(x\left(t_{n+p}\right)\right) \tag{6}$$

$$w_{p+1}^{'} = w_p^{'} + 2 * \mu * e(p) * x\left(t_{n+p-1}^{'} + 1\right) \tag{7}$$

$$w_{p+1}^{''} = w_p^{''} + 2 * \mu * e(p) * x\left(t_{n+p-1}^{''} + 1\right) \tag{8}$$

3 Prediction of information popularity

The goal of popularity prediction is to predict the exact number of retransmissions of a message at a certain time. The gray system theory believes that a sequence of ordered sums of obtained experimental data or observation data arranged by a certain rule. The initial data sequence contains traces of all other variables that are truly involved in the dynamic process of the system [Yang, Huang and Zhang (2017)]. The gray system method is a set of methods developed for systems with incomplete information, using explicit and hidden information in fewer datas. This paper defines the information sequence as X = {x_1, x_2, …, x_n}, and predicts the information popularity h_{t+1} at a certain future point in time [Liu, Li and Yang (2017)].

(1) Accumulated generating operation [Liu, Liu, Yan et al. (2019); Liao, Liang and Feng (2017)]: The data in the same sequence are sequentially added to generate new datas. Set the initial data be $X^{(0)}=\{x^{(0)}(1),x^{(0)}(2),\cdots,x^{(0)}(n)\}$, the accumulated generating operation sequence is $X^{(1)}=\{x^{(1)}(1),x^{(1)}(2),\cdots,x^{(1)}(n)\}$, among them, $x^{(1)}(k)$ is an accumulation of $x^{(0)}(k)$ and is called 1-AGO.

(2) Inverse accumulated generating operation: The accumulated generating operation inverse operation performs a different operation on the two datas before and after the data sequence [Yang, Zhang and Yang (2016)]. Let the initial data be $X^{(0)}=\{x^{(0)}(1),x^{(0)}(2),\cdots,x^{(0)}(n)\}$, inverse accumulated generating operation sequence is $Y=\{y(1),y(2),\cdots,y(n)\}$, among them, $y(k)$ is an inverse accumulated generating operation of $x^{(0)}(k)$ and is called 1-IAGO.

(3) Mean accumulated generating operation: The accumulated generating operation sequence is $X^{(1)}=\{x^{(1)}(1),x^{(1)}(2),\cdots,x^{(1)}(n)\}$, the mean accumulated generating operation sequence is $Z^{(1)}=\left\{z^{(1)}(1),z^{(1)}(2),\cdots,z^{(1)}(n)\right\}$, and $z^{(1)}(k)=0.5\left[x^{(1)}(k)+x^{(1)}(k-1)\right],k=2,3,\cdots,n$, $z(k)$ is a mean accumulated generating operation of $x^{(1)}(k)$ [Li, Li and Gao (2017)].

Definition 1: $\frac{dx^{(1)}}{dt}+ax^{(1)}=b\left(x^{(1)}\right)^2$ is the gray Verhulst model of the 1-AGO sequence $x^{(1)}(k)$, and the corresponding gray differential equation is $x^{(0)}(k)+az^{(1)}(k)=b(z^{(1)}(k))^2$, where a is the development coefficient and b is the gray interaction amount [Wang, Gu, Liu et al. (2019)].

Definition 2: $x^{(0)}$ is called a discrete non-negative initial data sequence, $X^{(1)}$ is a 1-AGO sequence of $X^{(0)}$, $Z^{(1)}$ is the mean accumulated generating operation, the least-square of the parameter sequence of the grey Verhulst model satisfies:

$$\begin{bmatrix} a \\ b \end{bmatrix}=\left(B^{\mathrm{T}}B\right)^{-1}B^{\mathrm{T}}Y \tag{9}$$

$$B=\begin{pmatrix} -z^{(1)}(2) & \left(-z^{(1)}(2)\right)^2 \\ -z^{(1)}(3) & \left(-z^{(1)}(3)\right)^2 \\ \vdots & \vdots \\ -z^{(1)}(n) & \left(-z^{(1)}(n)\right)^2 \end{pmatrix}, Y=\begin{pmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{pmatrix} \tag{10}$$

The corresponding solution of the whitening equation of the gray Verhulst model is

$$\hat{x}^{(1)}(t)=\frac{ax^{(1)}(1)}{bx^{(1)}(1)+\left(a-bx^{(1)}(1)\right)e^{a(t-1)}} \tag{11}$$

The discrete sequence value corresponding to the gray Verhulst model can be expressed as

$$\hat{x}^{(1)}(k+1)=\frac{ax^{(1)}(0)}{bx^{(1)}(0)+\left(a-bx^{(1)}(0)\right)e^{a(k-1)}} \quad k=1,2,\cdots,n \tag{12}$$

Based on the accumulation, the popularity of the next time is predicted. The prediction equation is as follows:

$$\hat{x}^{(0)}(k+1)=\hat{x}^{(1)}(k+1)-\hat{x}^{(1)}(k) \quad k=2,\cdots,n \tag{13}$$

When k<= n, $\hat{x}^{(0)}(k+1)$ is called the simulation value of the model, and when k>n, $\hat{x}^{(0)}(k+1)$ is called the predicted value of the model.

The posterior difference method is generally used to test the model：

$$S_1=\frac{\sqrt{\sum\left(\varepsilon_i-\bar{\varepsilon}\right)}}{n-1}, \bar{\varepsilon}=\frac{\sum\varepsilon_i}{n} \tag{14}$$

$$\varepsilon=\left|\hat{X}-X^{(0)}\right| \tag{15}$$

$$S_2=\frac{\sqrt{\sum\left[X^{(0)}(k)-\bar{X}^{(0)}\right]^2}}{n-1} \tag{16}$$

$$\bar{X}^{(0)}=\frac{\sum\bar{X}^{(0)}(K)}{n} \tag{17}$$

$$c=\frac{s_1}{s_2} \tag{18}$$

Model test accuracy range c: >0.35 excellent, <0.5 pass, <0.65 barely pass, >0.65 fail.

This paper applies the basic theory of the grey Verhulst model to the popularity prediction of network information transmission. The prediction process is as follows: First, the current transmission information is serialized to form the initial data sequence; and then based on the initial data sequence, constructs an accumulated generating operation sequence and a mean accumulated generating operation sequence, and then the parameters are estimated based on the gray theory model to predict the popularity of the information at the next moment to control the latest spread of the information. The prediction framework based on the gray theory is shown in Fig. 2.

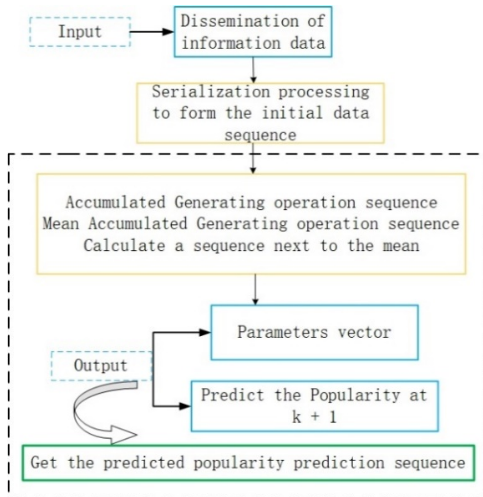

Figure 2: The prediction framework based on grey theory

The input of the information transmission popularity prediction model is historical behavior data $Q=\{(q,t)\mid t\in\varphi, t<=t_k\}$ of the previous k time, where (q, t) represents the retransmission volume of time t is q, φ represents the life cycle of network information transmission.

Network information popularity prediction algorithm
Input: Historical behavior data $Q=\{(q,t)\mid t\in\varphi, t<=t_k\}$
Output: Parameter a and b, Popularity in the next period
1 : Serializing to form the initial data sequence $X^{(0)}=\{x^{(0)}(1),x^{(0)}(2),\cdots,x^{(0)}(n)\}$;
2 : Calculating one accumulated generating operation sequence $X^{(1)}=\{x^{(1)}(1),x^{(1)}(2),\cdots,x^{(1)}(n)\}$;
3: Calculating a sequence next to the mean $Z^{(1)}=\left\{z^{(1)}(1),z^{(1)}(2),\cdots,z^{(1)}(n)\right\}$;
4 : Computing parameter a and b;
5: Predicting the popularity of the next time;
6: Getting the predicted popularity prediction sequence $\hat{X}^{(0)}=\left\{\hat{x}^{(0)}(1),\hat{x}^{(0)}(2),\ldots,\hat{x}^{(0)}(k),\ldots,\hat{x}^{(0)}(n)\right\}$;

4 Experiment analysis

The experimental simulation environment of this paper is Matlab 2019b. The machine is Dell, CPU: i5 3.2G, RAM: 4G. The operating system is WinXP. The measured data set is from topics in the Sina Weibo topic list. Using web crawler technology to crawl Weibo topics, the data time is 2019. 1. 25-2019. 12. 31. Verify the validity of the gray Verhulst model in popularity prediction. The following table lists the data of the topics:

(1) Feature crawl

The list of popular topics provided by Sina Weibo can cover all the concerns of people in society. The datasets obtained in this experiment by crawling the list. At the same time, crawling topic reading volume is used as a reference for topic popularity.

(2) Web crawler

Using the requests library and other modules to write a crawler program, obtaining data from the Sina Weibo WAP terminal. In order to cope with the possible anti-crawling mechanism, the camouflage method of setting headers and IP proxy is adopted to ensure the smooth progress of the crawler.

Table 1: Network topic information

Topic source	2019 Movie released 《Crazy Alien》
Acquisition time	2019.1.25-2019.12.31
Active users	3600
Alternate users	84578
Number of active user behaviors	78900
Number of Alternate user behaviors	1524457
Network edges	1368120

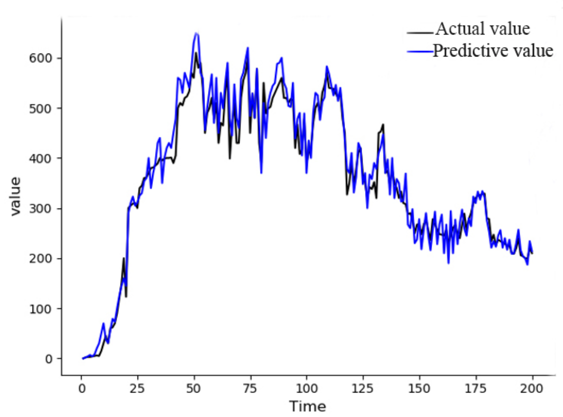

Figure 3: Experimental diagram of adaptive prediction

To test the prediction effect of the adaptive prediction model, we compare the true value with the adaptive prediction model according to the information in the Tab. 1, as shown in Fig. 3, select two hundred time points of the topic and observe the changes in the transmission situation.

It can be seen that our proposed adaptive prediction model for network information transmission has better prediction results, the prediction data of the first two hundred time points of the experiment are almost consistent with the trend of actual values. The adaptive prediction method proposed in this paper can make very good predictions of chaotic sequences with few training samples.

To evaluate the effectiveness of the popularity prediction algorithm, using mean absolute error (AE), mean square error (SE), and mean absolute percentage error (APE) to evaluate the popularity prediction algorithm. It can be expressed as follows:

$$AE = \frac{1}{n}\sum_{k=1}^{n}\left|\varepsilon^{(0)}(k)\right| \tag{19}$$

$$SE = \frac{1}{n}\sum_{k=1}^{n}\left(\varepsilon^{(0)}(k)\right)^2 \tag{20}$$

$$APE = \frac{1}{n}\sum_{k=1}^{n}\left|\frac{\varepsilon^{(0)}(k)}{x^{(0)}(k)}\right| * 100\% \tag{21}$$

The auto-regressive integral moving average model ARIMA and moving average model MA are compared with the gray Verhulst model used in this experiment to verify the effectiveness of the model. The evaluation criteria are shown in Tab. 2.

Table 2: Comparison of evaluation criteria for the popularity of different models

Model	AE	SE	APE
GM（1，1）	20.10	1521.33	378.45
ARIMA	20.03	1282.23	164.55
MA	26.12	2130.75	171.83
Gray Verhulst	17.10	1034.34	67.68

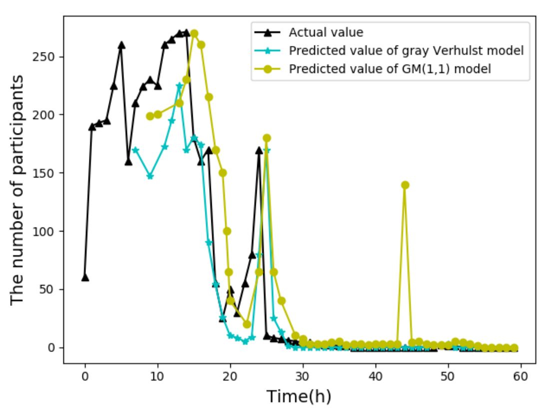

Figure 4: Comparison of popularity prediction between gray Verhulst model and GM (1,1) model

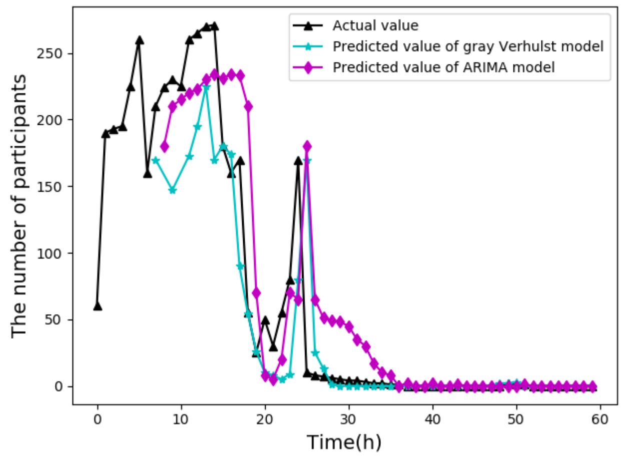

Figure 5: Comparison of popularity prediction between gray Verhulst model and ARIMA model

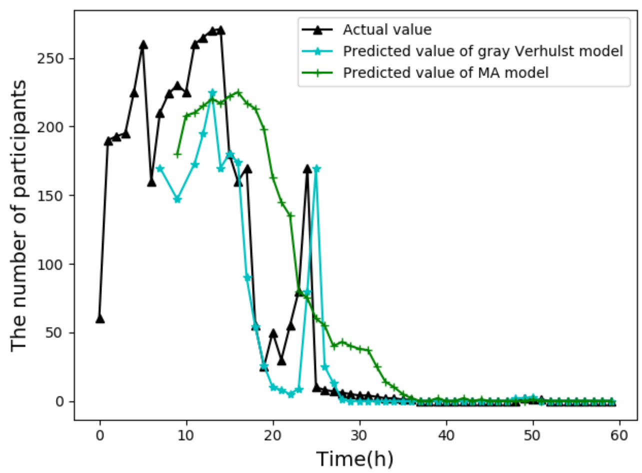

Figure 6: Comparison of popularity prediction between gray Verhulst model and MA model

This paper graphically displays the prediction results of each model. The abscissas of Figs. 4-6 are time (in hours), and the ordinates are the number of participants in the topic. By observing Fig. 4-6, it can be found that the same conclusions as in Tab. 2, the four models used in the experiments are all good prediction models. However, in terms of the fitting effect, the gray Verhulst model proposed in this paper and the popularity of the network information. The actual value is the closest, and the fitting effect is well, the development trend of the transmission situation in a period is better characterized.

5 Summary

The research on the perception and prediction of the law of information transmission is one of the hotspots in the field of social computing. This paper mainly studies the adaptive prediction model and the popularity prediction algorithm based on the gray Verhulst model. First, it introduces the basic idea of information transmission perception, then the adaptive adjustment strategy is used to construct an adaptive prediction model for information transmission awareness to predict and analyze the development law of information transmission. The conclusion indicates that the adaptive prediction model proposed in this paper has good prediction results. At the same time, this paper combines the gray system theory algorithm to serialize the current transmission information to form the initial data sequence; and then builds the accumulated generating operation sequence and the mean accumulated generating operation sequence based on the initial data sequence, estimates the parameters and predicts the popularity of the next moment of information based on the gray theory model. To evaluate the effect of the algorithm, three evaluation indexes are also proposed. Experiments show that using the gray Verhulst model to predict the topic's popularity in the future can grasp the development trend of the topic, and comparison with several other prediction models shows that the fitting effect on the popularity of the information is well. Therefore, the model based on the gray system theory is a popular prediction model with a good prediction effect and strong versatility.

Acknowledgment: The authors gratefully acknowledge the financial support provided by the Key Laboratory of Hunan Province for New Retail Virtual Reality Technology (2017TP1026).

Funding Statement: This work was supported by the National Natural Science Foundation of China (61772196; 61472136), Hunan Provincial Natural Science Foundation (2020JJ4249), Key Project of Hunan Provincial Social Science Foundation (2016ZDB006), Key Project of Hunan Provincial Social Science Achievement Review Committee (XSP 19ZD1005), Postgraduate Scientific Research Innovation Project of Hunan Province (CX20201074).

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

References

Cui, Y.; Song, J.; Miao, C. C. (2017): Mobile cloud computing research progress and trends. *Chinese Journal of Computers*, vol. 40, no. 2, pp. 273-295.

Ghosh, S.; Shekar, S. K. (2017): Video popularity distribution and propagation in social network. *International Journal of Emerging Trends & Technology in Computer Science*, vol. 6, no. 1, pp. 1-5.

Gao, Q.; Sun, C.; Yang, C. (2014): The influence of network structural properties on information dissemination power in microblogging systems. *International Journal of Human Computer Interaction*, vol. 30, no. 5, pp. 394-407.

Hu, Y.; Hu, C. J. (2016): Predicting the popularity of viral topics based on time series forecasting. *Neurocomputing*, vol. 210, no. 4, pp. 55-65.

Huang, D.; Zhou, J.; Yang, F. (2015): Understanding retweeting behaviors in twitter. *Journal of Computational Information Systems*, vol. 11, no.13, pp. 4625-4634.

Jiang, W. J.; Wang, Y.; Jiang, Y. R.; Chen, J. H.; Xu, Y. H. (2019): Research on mobile internet mobile agent system dynamic trust model for cloud computing. *China Communications*, vol. 16, no. 7, pp. 174-194

Liao, Z. F.; Liang, J. B.; Feng, C. C. (2017): Mobile relay deployment in multihop relay networks. *Computer Communications*, vol. 112, no. 1, pp. 14-21.

Li, J. R.; Li, X. Y.; Gao, Y. Q. (2017): Energy saving research on mobile cloud computing in 5G. *Chinese Journal of Computers*, vol. 40, no. 7, pp. 1491-1516.

Liu, Y.; Liu, L; Yan, Y.; Feng, H.; Ding, S. C. (2019): Analyzing dynamic change in social network based on distribution-free multivariate process control method. *Computers, Materials & Continua*, vol. 60, no. 3, pp. 1123-1139.

Liu, X.; Li, J. B.; Yang, Z. (2017): A task collaborative execution policy in mobile cloud computing. *Chinese Journal of Computers*, vol. 40, no. 2, pp. 364-377.

Liu, L.; Yang, C.; Liu, T. T. (2018): A classification method for micro-blog popularity prediction: considering the semantic information. *Advances in Swarm Intelligence*, vol. 10942, no. 3, pp. 351-360.

Liu, Y. B.; Zhao, J. B.; Xiao, Y. P. (2018): C-RBFNN: a user retweet behavior prediction method for hotspot topics based on improved RBF neural network. *Neurocomputing*, vol. 275, no. 7, pp. 733-746.

Tan, Z.; Wang, Y.; Zhang, Y. (2016): A novel time series approach for predicting the long-term popularity of online videos. *IEEE Transactions on Broadcasting*, vol. 62, no. 2, pp. 1-20.

Wang, J.; Gu, X. J.; Liu, W.; Sangaiah, A. K.; Kim, H. J. (2019): An empower Hamilton loop-based data collection algorithm with mobile agent for wsns. *Human-centric Computing and Information Sciences*, vol. 9, no. 1, pp. 1-14.

Wang, J.; Jiang, C.; Qian, J. (2014): Robustness of interdependent networks with different link patterns against cascading failures. *Physical A: Statistical Mechanics and Its Applications*, vol. 393, no. 5, pp. 535-541.

Wang, H.; Li, Y. P.; Feng, Z. N. (2013): Re-tweeting analysis and prediction in microblogs: an epidemic inspired approach. *China Communications*, vol. 10, no. 3, pp. 13-24.

Xiao, A.; Liu, J.; Li, Y. (2018): Two-phase rate adaptation strategy for improving real-time video QoE in mobile networks. *China Communications*, vol. 15, no. 10, pp. 12-24.

Yang, J.; Counts, S. (2010): Predicting the speed, scale, and range of information diffusion in twitter. *International Conference on Weblogs and Social Media*, vol. 10, no. 4, pp. 355-358.

Yang, Z.; Guo, J.; Cai, K. (2010): Understanding retweeting behaviors in social networks. *Proceedings of the 19th ACM International Conference on Information and Knowledge* Management, pp. 1633-1636.

Yang, X.; Huang, D. C.; Zhang, Z. K. (2017): Neighborhood coreness algorithm for identifying a set of influential spreaders in complex networks. *KSII Transactions on Internet and Information Systems*, vol. 11, no. 6, pp. 2979-2995.

Yang, F.; Zhang, R. S.; Yang, Z. (2016): Identifying the most influential spreaders in complex networks by an extended local k-shell sum. *International Journal of Modern Physics C*, vol. 28, no. 1, pp. 925-214.

Zhang, W. L.; Guo, B.; Shen, Y.; Wang, Y. (2016): Computation offloading on intelligent mobile terminal. *Chinese Journal of Computers*, vol. 39, no. 5, pp. 1022-1038.