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Design and Development of Logistic Artificial Neural Network for Electronic Commerce

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Abstract: This study shows that logistic neural network can be a better alternative to diffusion modeling of technological innovation including electronic commerce in the neural network based integrated approach predicts and models the diffusion of technology innovation. Especially, diffusion model by logistic neural network shows better performance through discussion of different diffusion related dynamics such as internal and external influence of growth process and comparison of traditional diffusion theory.

The results of this study can be applied to other similar technologies as well as e - commerce growth modeling.

Index Terms: Logistic neural network, Mixed model, Real-Time Scheduling, CAN communication.

I. INTRODUCTION

There are two problems in forecasting, measuring and tracking the global diffusion problem of e-commerce [1,3]. First, an appropriate model for understanding and predicting diffusion phenomena for planning. Second, growth is measured by the diffusion of technological innovation. However, in the case of a specific product, it is possible to make a clear measurement of the diffusion in relation to technological progress.

Artificial neural networks have the advantages of flexibility and noise sensitivity compared to traditional methods. Artificial neural networks are flexible in that they search for signals contained in the data without using a one-dimensional relationship determined first. It also does not require any assumptions about the distribution of data. However, neural network models cannot always be generalized in most applications.

Especially, as a problem of artificial neural network, first, there is a problem in prediction by surrounding factors when it is not designed to be suitable for the environment to be used.

Second, most of them have unnecessary training data.

When learning the growth pattern of e - commerce, we need a mathematical function that represents the output relation of the correct inputs. When used as an alternative to traditional models, the artificial neural network model should have at least the accuracy of the traditional ones.

In this respect, research on e-commerce diffusion modeling is highly desirable. These studies use a mixed model of a combination of a traditional diffusion model and a neural network model.

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In this study, an integrated approach based on artificial neural network predicts the spread of technological innovation. Especially, it is confirmed that logistic artificial neural network can be a better alternative to diffusion model of technological innovation including electronic commerce.

The results of this study can be applied to growth modeling by e-commerce growth modeling as well as other similar technological innovations.

Also, in the presence of external influences, artificial neural network based models are more realistic than traditional models.

II. COMBINATION OF TRADITIONAL DIFFUSION MODEL AND ARTIFICIAL NEURAL NETWORK

When it is divided into four important forms of e-commerce, it can be divided into online infrastructure, application, relay, electronic commerce and so on. These forms consist of companies that play a key role in creating and activating an online economy [2],[4]. The organizations that make up the infrastructure provide products and services needed to build an IP-based network.

Application-related companies enable products and services in an Internet-based structure to enable business activities online across the network.

Interpreters gain the so-called price of Internet transactions by promoting interaction between consumers and producers through market activities such as confirmation and compromise.

E-commerce is made up of companies engaged in all activities involved in selling products and services for consumers or businesses through the Internet, and it gives economic value to the traditional value chain.

The diffusion model of technological innovation includes two main assumptions. First, the number of existing technology prisoners is positive for the growth rate, and second, for the difference between the number of potential prisoners and the number of prisoners in the saturated state, or the rate of growth. Two basic theories are used to explain the logical elements behind the model set-up.

This diffusion model uses the logistic curves and corresponding pseudo-curves as a basis and therefore does not adequately reflect external factors due to government interference, etc.

This leads to a rapid change in diffusion rate. However, because the approach to diffusion model starts with a previously selected parameter function, the flexibility of the modeling technique drops. In the measurement process of the

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diffusion model, we try to fit the data in a way that adjusts the values of the parameter of the form. If diffusion growth ceases for a while due to external factors, then the logistic curve should start with a flat state rather than a curve due to regrowth. Diffusion modeling can be a flexible approach if e-commerce growth is involved in government and affected by external factors such as security issues.

As a general method of diffusion process, three kinds of internal influence model, external influence model and mixed influence model can be applied [3],[5].

The mixed influence model represents both internal and external influences in the diffusion process and can be defined as Equation (1).

$$dY_t/dt = (p + qY_t)(K - Y_t) \tag{1}$$

Where K is the potential number of prisoners due to technological innovation, Y_t is the cumulative sum of prisoners at time t, p is the coefficient of external influence, and q is the coefficient of internal influence.

The advantage of artificial neural networks is that they adequately deal with the noise of spread data made up of external factors in modeling complex patterns.

The nonlinear regression model of the feedforward neural network having one hidden layer is defined by the following equation (2).

$$\log \hat{y}_{t+h} = \hat{\beta}_{\phi h} + \sum_{j=1}^{n} \hat{\beta}_{jh} f(I_t, \hat{w}_{hj}) \tag{2}$$

Where I_t is the input vector at the current time, h is the prediction limit, h is the estimate of w, the network weight corresponding to the j-$_{th}$ hidden node, and the number of hidden nodes is n. The logistic transfer function at each node is given by the following equation (3).

$$f(I_t, \hat{w}_{hj}) = 1/(1 + e^{-z}), \quad z = \hat{w}_{hj\phi} + \hat{w}_{hj} t \tag{3}$$

Artificial neural networks have advantages over traditional diffusion models and flexibility in generating nonlinear boundaries that distinguish different predictive values in multidimensional input space.

In order to capture complex phenomena such as e-commerce diffusion, we can propose e-commerce diffusion modeling based on the robustness of neural networks, applying a pure neural network model and a mixed model combining the advantages of traditional models with neural networks.

In particular, the best of the traditional models has been studied as a logistic model [4],[6].

In the statistical method, it is desirable to set the inverse of the root-mean-square value for different predictions to a weight [5],[12]. This approach minimizes dispersion of the prediction error. When various prediction schemes are used, the combination of these schemes is given by the following equation (4).

$$N_M(t) = \Sigma_{m \in M} W_{mt} F_m(t) \tag{4}$$

Where m is the prediction method, M is the total number of prediction methods to be combined, $F_m(t)$ is the predicted value by the method of m at a particular time t, $N_M(t)$, W_{mt} is a weight on the predicted value by the method of m in t. If there is no weight change in t, we can use W_m as the following equation (5).

$$W_m = (1/\text{MSE}_m)/(\Sigma_{m \in M}(1/\text{MSE}_m))$$
$$\text{MSE}_{m,C} = [\Sigma_{t \in C}(F_m(t) - y_t)^2]/N \tag{5}$$

y_t is the actual value at a specific time t, and N is the predicted value at the entire measurement time. The above equation (5) determines the relative weights by the base models in generating the mixed model based on the MSE value. The MSE of one model has a lower MSE than the other model, and has a higher weight. If one of the models shows a distinct performance than the other, we can ignore the weaker model and give a weight close to 100%.

The biggest problem in applying this mixed model is that the traditional diffusion model is based on parameter statistics, but the neural network model is not capable of statistical testing with a non-parametric approach the number of neurons in the layer is limited to three. However, given the random appearance of external influences, the application of the neural network with the form of exponential function as a transfer function may perform better than the combined form of traditional logistic diffusion model and neural network. In addition, when the number of neurons in the hidden layer is 4 or more, the possibility of over-fit cannot be ruled out, but the predictive power of the model is remarkably increased.

III. DESIGN OF LOGISTIC ARTIFICIAL NEURAL NETWORK

The traditional model of e-commerce diffusion shows that logistics is the best reflection of internal effects. It is shown that the application of logistic model shows better performance in connection with the conventional diffusion model and neural network combination.

However, as discussed in Chapter 2, constraints on the number of neurons in the hidden layer are problematic due to the poor predictability of models due to under correction, errors due to relative weighting, and considerable computation time requirements due to the combination of different prediction methods.

This chapter mitigates these problems and designs a high performance logistic artificial neural network (LANN) as an integrated model.

A. Logistic artificial neural network design

The artificial neural network has layers composed of linear and nonlinear functions and has a structure composed of each function is fed back in selected order. The weights on each layer of the network are updated.

In this study, only one hidden layer is considered, logistic function is used as the transfer function, and linear function is used as the output layer. The reason is application of regression equation of neural network about continuous output.

The artificial neural network enables to reflect the spread of electronic commerce by using logistic function. A layer of logistic is added to the end of the process. That is, output from the linear layer is inserted to identify e-commerce spread.

Thus, the probability p_{nj} for class j is determined according to the following equation (6) to calculate the output w_{nj} of the linear layer with respect to the specific data n.

$$p_{nj} = \exp(w_{nj}) / \sum_k \exp(w_{nk}) \quad (6)$$

The difference between the logistic neural network and the pure neural network to be designed in this paper is that the pure neural network determines one attribute value as a function of the other properties while the logistic neural network identifies the e - commerce diffusion. Therefore, it is not to minimize the difference between the actual value of the object of interest and the predicted output value, but to minimize the diffusion identification error of the training data. A logistic model application step is added to the iterative process of updating the weights with an ideal value. This affects the logic used for classifying the new data as well as the logic used for model training. Two functions are used to perform feedback during network training. One minimizes the likelihood of the data's negative likelihood, and the other minimizes the negative likelihood ratio gradient direction to support the optimization algorithm. There are some issues related to the development of logistic neural networks. First, standardization of input data is required.

After normalizing the input data, the initial weighting matrices *V* and *W* are set to uniform random numbers between -0.01 and 0.01.

This task is to ensure that the network does not minimize the weights *V* and *W* in the same way. The weights apply the scaled conjugate gradient descent (SCGD) algorithm, which minimizes the likelihood likelihood function repetitively and determines the next likelihood direction using the slope function. Critical columns should be added after standardization since they must be added before standardization. The weights are determined in a manner that minimizes the difference between the actual and predicted values, and iterates through the updating of the weights in such a manner that the difference between the target and the predicted value is calculated each time and has an error within the tolerance.

Here, the SCGD algorithm is called to find a local minimum point for the difference between the actual and predicted values. The SCGD algorithm is repeated until the specified maximum number of iterations or the minimum point is reached. Each time the SCGD algorithm is iterated, the weights change the weights to reach the local minimum. In relation to the SCGD algorithm performance, it is necessary to compute the difference between the actual and the predicted values, and to write two functions that can perform the slope calculation. One is to calculate the difference between the actual and predicted values based on the model's current iteration performance.

One area of interest in the application of logistic artificial neural networks is the determination of appropriate hidden node layers. That is, it is the determination of the appropriate hidden nodes. The model does not capture e-commerce spread when very small hidden nodes are used. Conversely, however, the determination of too many hidden nodes will result in a greater error in the test and review data set due to the over-fit of the training. Weight reduction can be used as a technique that balances the over-fit of the model.

In relation to the current iteration of the model, another function is needed for the slope calculation function on the weights. The slope function uses a weight similar to the above function. The weights are decomposed into the weight *V* of the hidden layer and the weight *W* of the output layer. The weights are used with standardized inputs to calculate the difference from the actual value as well as the predicted value. The value of the difference is applied to the slope function. The slope function calculation is as follows. In the equation of the slope calculation, a variable having a symbol of "~" indicates the use of all the columns including the critical column and the critical weight, and a variable of the symbol "^" indicates the case where the critical column is removed. (See equation (7))

$$\nabla v = -\frac{1}{NK}(\tilde{x}_s)^t \sum_k (t_k - g_k)(\hat{w})^t (1 - z^2) + \lambda v^2$$
$$\nabla w = -\frac{1}{NK}(\tilde{z}_s)^t \sum_k (t_k - g_k) + \lambda v^2 \quad (7)$$

Where *N* and *K* denote the number of data and class, respectively. Since the output node weight *w* has one more row than the output node since it uses the threshold weight, the calculation of the slope *v* does not use the critical weight. When the SCGD algorithm converges, the concealment and output weights are returned, and these weights are decomposed and returned to the function called with the normalization function [6,7,14,15,16,17].

IV. COMPARATIVE TEST

In this study, we used the number of hosts in the dot-com domain by Mukhopadhyay et al. [4] for comparison with the proposed neural network.

The data used in the comparison test is the total number of Internet sites within the dot-com domain described in the report published by Netcraft. (From August 1995 to July 2004). For more information, see www.netcraft.com [Netcraft, 2004]. Because there can be multiple sites on the same machine or multiple machines on a single popular site, Netcraft's aggregation is based on different domain names than on computer algebra.

First, Figure 1 shows the fit by logistic function, a traditional diffusion model.

The parameters of the logistic function were determined by nonlinear least squares method including nonlinear data fit. In particular, we use the subspace trust region method based on the interior-reflective Newton method to improve accuracy than that of Mukhopadhyay et al.

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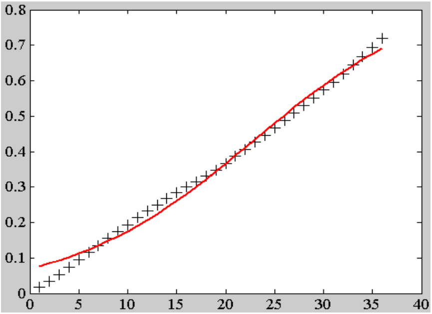

Figure 1: Fit of logistic model

Figure 2 shows the result of convergence to sse = 0.016078 after 60 iterations when K = 1, A = 0.1, B = 0.3. The final parameter estimates are K = 1.1604, A = 13.1333, and B = 0.8993. The reason for the difference between the parameter estimates and those by Mukhopadhyay et al. Is the result of standardizing the data for the application of the logistic neural network. As for the standardized data, the sse value according to the application of the logistic model by Mukhopadhyay et al. Is 0.0362, suggesting that the subspace trust region method of this study increases the prediction accuracy.

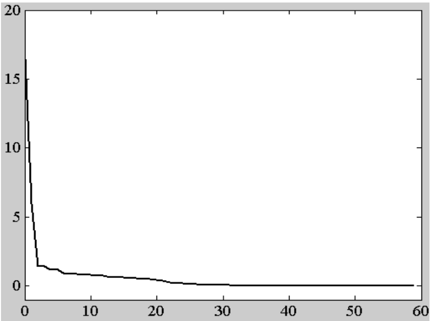

Figure 2: Subspace trust region convergence

[Figure 3] shows the result of applying the mixed model by Mukhopadhyay et al., In which case sse = 0.0104 shows better performance than using the traditional logistic diffusion model. Given the scaling of approximately 10-9 according to data standardization, the mixed model with neural networks is more flexible in predicting the diffusion of electronic commerce, especially when external factors influence diffusion.

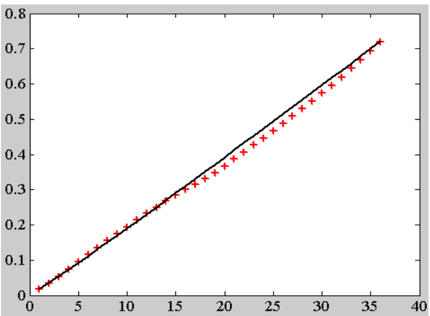

Figure 3: Fit of logistic model

Finally, [Figure 4] shows the fit result by the proposed logistic neural network. In the hidden layer, three hidden nodes are used, and the λ value for weight reduction is 0.001.

SSE shows very good performance with 3.4985e-006 after 100 iterations as shown in the upper figure of [Figure 4]. For reference, five different S-curves with 100 observations were generated as in Mukhopadhyay et al., In order to enhance the validity of our new approach to e-commerce proliferation modeling. The first set of data is the basic case where there is no external impact at all and only internal factors affect the diffusion rate.

The data used random numbers generated from the S-curve with some random noise as a virtual cumulative sum of the number of dot-com hosts in millions of units. The second dataset is similar to the first one, but the values starting around the inflection point were increased by 5%. The third through fifth data sets are similar to the second one, but are configured to increase the magnitude of the upward change. That is, they start at the same time period and have incremental rising points of 10%, 15%, and 20%, respectively.

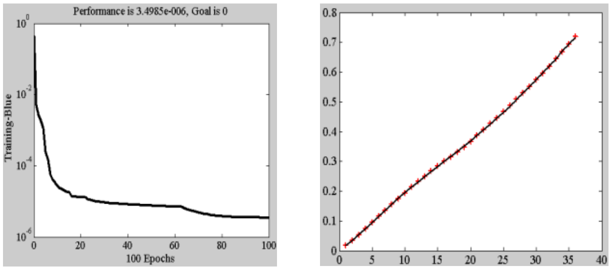

Figure 4: Logistic neural network fit

When comparing the performance of the logistic and mixed models for these five data sets, the mixed model always showed better performance, though not a big difference, and compared to the logistic neural network model, the difference between the SSE values is very large, In the case, the logistic neural network model overwhelmed other models. When applying a dramatic increase in the number of dot-com hosts around the inflection point for each simulated data set, the curve fit in the logistic model showed a gentle curve shape, ignoring the change. The morphological parameter value does not reflect enough rapid changes. On the other hand, the logistic neural network updated the weights in a way that immediately reflects the continuing aspect of diffusion with rising change.

In conclusion, traditional models do not detect changes due to external influences, but logistic neural networks can detect changes that occur after one cycle and have immediate strengths that can be adjusted.

V. CONCLUSION

The internal impacts associated with e-commerce diffusion modeling are discussed in depth in the literature.

Most of these models are modified forms of the S-curve. The problem is that the external impact is large, but mostly ignored. The reason is that at some life cycle stage, external influences are likely to be region dependent.

In the simulation by Mukhopadhyay et al. For the feasibility study of the mixed model, we do not deal with the problem of under- or over-fit, but according to our experiments, some of the five test sets have under-fit problems. The proposed logistic neural network model can be an effective approach to theoretically unidentified problems that are suspected of external influences. In particular, it is possible to increase the predictive power by preventing the problem of over-or under-fit by using several nodes in the hidden layer.

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