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A HDNN Model to Foretell the Growth of Electronic Commerce

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Abstract

There are humpty numbers of companies available in determining and forecasting the development of e-commerce. The further most difficulty slouches in deciding a forecasting model that can have influences on diffusion. Here, it is proposed a model, Hybrid Diffusion (HD) and Neural Network (NN). This involves traditional diffusion and artificial neural networks. The proposed model incorporates the two into a hybrid model in order to study e-commerce growth. For the growth of e-commerce, a dot com count has been used a reliable measure.

Key Words: E-commerce, neural network, HDNN and diffusion models.

1. Introduction

Mathematics is ever green. There is a need for Mathematical Models always all over the world. Not only towards pure Mathematics but also to all other fields for computational efficiency there is an urgent need for the improvements in the existing models. Recently [7] proposed an SODE model for dengue fever and the same has been enhanced by [Srinivasan, et. al., 2014]. Hence, the problems are the sole property mathematics in all the fields. Now, globally, e-commerce faces two important problems; the first one is modeling the diffusions and the second one measuring the growth. With few limitations, [Gurbaxani, 1990] and [Mahajan, et.al., 1998] proposed few measurements. Here, it involves the issue of e-commerce along with diffusion problems in growth. One can assume from Fourt & Woodlock (1960), that the growth rate of adoption is constant. Simple logistic curve follows a diffusion process with the limitation over time, stated by Mansfield (1961). Due to humpty number of external factors, viz., security, changes in amendments, etc., affects the truthfulness of model. Therefore, the sense is more diffusion. The Neural Network (NN) or Artificial Neural Network (ANN) gives the logical alternatives for modeling the traditional one. If NN-based models do not carry out in a different way from conventional ones, one may conclude that manipulate on diffusion are purely domestic in nature. The domino effects of this work offer other views of modeling the augmentation of pioneering products in general and in particular, the growth of e-commerce. It would offer a crystal clear way to handle external and internal control together in the same model.

2. Modeling

The adoption of new innovations or technologies generally does not progress in a beautiful liner fashion, and studies of the phenomenon have focused on explaining the reasons for this. The diffusion rate is defined as the speed at which members of a social system adopt the innovation. First, the existing number of adopters (of the innovation) positively drives the rate of growth. Second, the difference between the potential number of adopters at the saturation level and the number of existing adopters also influences the rate of growth. Two basic diffusion theories have been used in the literature to explain the logic behind these models. First, the diffusion of innovation theory [Rogers, 1983], which studies diffusion as a process by which an innovation is communicated internally over time among the members of a social or market system. The second, utility theory of social networks [Valente, 1996], suggests that potential returns from adopting a network depends on the number of existing users. Two mathematical specifications of S-curve models – Gompertz and logistic – were used most widely in studies of diffusion growth rates [Gurbaxani, 1990]. [Rai. et al. 1998] also uses the exponential function in addition to the Gompertz and logistic functions. Exponential curves assume a constant ratio of growth rate that generally characterizes the early stage of an innovation, and do not force a reduction in growth rage like the S-curves. While these methods have been appropriate for modeling diffusion that follows some variant of the S-curve, they fail to capture external effects on the adoption growth rates. The ability of the NN to model complex patterns should make it ideal in dealing with disturbances in diffusion data due to external effects. Motivated by its robust capability in capturing complex phenomenon, it is to examine two NN based approaches that can be considered novel for the purpose of modeling diffusion of innovation: a hybrid model that combines the NN model with the best of the traditional ones.

3. The Hybrid Model

It is usually beneficial to combine forecasts from different forecasts [Russell et al. 1987]. Putting equal weighs on methods to combine is not recommended. Statistician's recommendation is to weight the forecasts from different methods by the inverse of individual methods Mean Square Error (MSE) [Armstrong 2001 p.423]. The method essentially minimizes the expected forecast error variances. It works best when the biases (direction of forecast – forecasting high or low) of the methods are in different direction. Therefore, combined the two approaches (or methods) as follows:-

$$\zeta\Gamma, t\epsilon\beta = \sum_{\gamma\epsilon\Gamma} \eta_{\gamma,t\epsilon\beta} * \varepsilon_{\gamma,t\varepsilon\beta} \quad \text{.........} \ (A)$$

Where

α_1 is the calibration time horizon

β is the forecast time horizon in future

γ is the forecasting method

Γ is the total number of forecasting methods being combined

$\varepsilon_{\gamma,t\varepsilon\beta}$ is the forecast from method γ for ***t*** in β

ζ is the new combined forecast from γ number of methods for ***t*** in β

$\eta_{\gamma,t\varepsilon\beta}$ is the weight on the forecast from method γ at ***t*** in β

Since weights were not varied at ***t*** in β and is given by

$$\eta_\gamma = [MSE_{\beta\gamma}]^{-1} \div \left[\sum_{\gamma\varepsilon\Gamma} MSE_{\beta\gamma}\right]^{-1} \quad \text{...............} \ (B)$$

$\theta_{t\varepsilon C}$ is the actual value of dot com counts over calibration horizon at time ***t*** in β

K_c is the number of predictions in β

$\varepsilon_{\gamma t\varepsilon\beta}$ Forecast from method γ for ***t*** in β

Equation (2) determines the relative weights of the two basic models in creating the hybrid model on the basis of their MSE values. The lower the MSE of a model relative to the other, the greater the weight it receives. If one of the models outperforms another strongly, it may receive a weight close to 100% discarding the weaker model.

4. Results and Analysis

It is used the number of hosts in the do-com domain as a measure of the diffusion of e-commerce infrastructure growth, consistent with the literature on diffusion studies involving the Bitnet [Gurbaxani 1990] and the Internet [Press, 1997; et. al., 1998]. It is collected the total number of live internet sites in the dot-com domain worldwide from August 1995-Feb 2013 form the reports published by Net craft on their web site www.netcraft.com [Net craft, 2013]. Net craft collects all the names of hosts that they can find on the Internet, and polls them with a request for the server name.

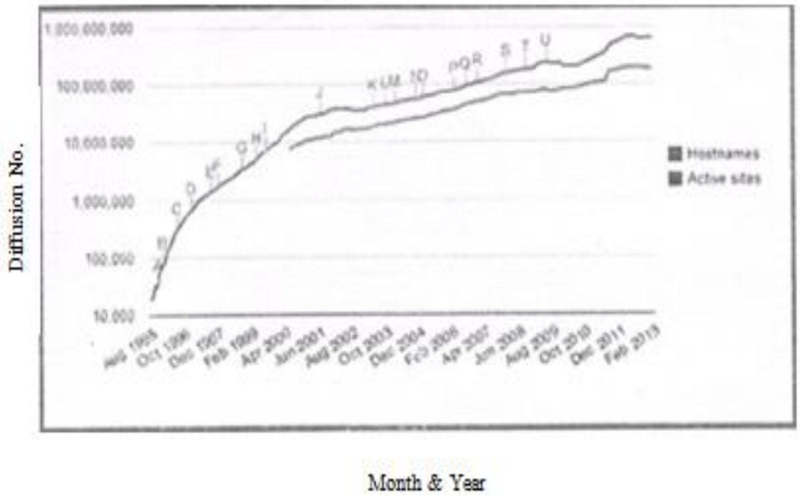


Figure 1: Data analyzed is form August 1995 to Feb 2013

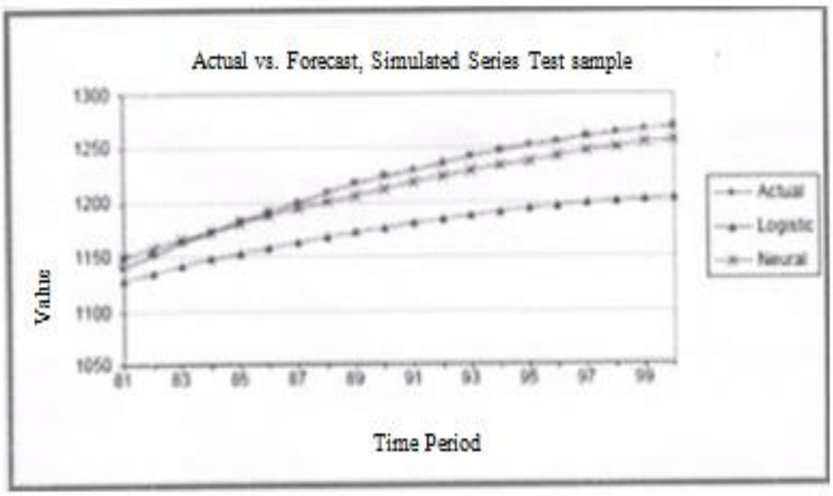
Here, it is used a two-step method to compare the predictive efficacy of the models. In step one, it is standardize our models. The methods used here for the above said efficacy is logistic. Finally, the ever youth model exponential is used on time series data. The time duration of the data analyzed is from August 1995 to Feb 2013. It is then used the next eighteen months of data to validate the traditional diffusion models. Before doing all these process the goempitz method is used to standardize the proposed model. The size of the test sample (typically about 20% of the total sample) is in line with recommendation from preceding literature [Bishop 1995]. It is built a multi-layered perceptron neural network model (which will refer as the ‘pure NN’ model, to distinguish it from the hybrid) to predict e-commerce growth on the same sample. The best diffusion model based on its performance. That should include both calibration and test samples. The further most steps are to test the samples. The NN model was then selected for the consequent analysis in step two.

In step two, it is combined the best step one diffusion model with the pure NN model to generate a hybrid model. It is compared the forecasting performances of these models: (a) the best diffusion model (b) NN model and (c) hybrid model. It is to be tested on a larger test sample. In order to calculate the performance, here it is used the root mean squared error (RMSE). RMSE is the most popular measure of recital while the necessity arises in comparing different methods in order to make a decision [Armstrong & Collopy 1992; Carbone & Armstrong 1982].

5. Simulation

The forecasts and RMSE of two of the models, namely logistic and NN on the test samples has been performed. For the simulated data, the relative performance of the logistic regression compared with the NN. It was too poor enough to render a weight of almost 0. Thus, the forecasts of the hybrid model were essentially the same as those of the NN model. The difference between the RMSE values for the NN model and logistic model is very high. The ability of the NN model to adapt to the spike in data results in better forecasting performance on the test data, as shown in the figure below.

It is simulated “drops” (5%, 10%, 15%, and 20%) in a similar way instead of “hikes”. As expected, NN did better than LL on all the simulations validating NN model’s superiority further in predicting the expected e-commerce growth.



Time Period

Figure 2: Actual vs. Forecast, Simulated Series Test Sample

6. Conclusion

This works makes a contribution to e-commerce research by symptomatic of a work of fiction approach to model its diffusion. Several studies discuss the idea of imitation, behavior and its effect on the diffusion of an innovation. External influences are largely ignored while modeling. This is perhaps because external effects can be domain-sensitive or occur at any stage of the life cycle. The proposed approach will be useful for most other innovation diffusion modeling studies. The model development may further be enhanced by the simulations cum theoretic approach.

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