

TOWARDS FORECASTING BUSINESS PREPAID MOBILE USING NEURAL NETWORK TECHNOLOGY

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Abstract : *Prepaid mobile service has become necessity to the society and contributed success to many businesses. In order to be sustained in mobile telecommunication (Telco) industries, carriers need to plan their businesses as to ensure the increase use of their products and services. One of the strategies that can be applied in Telco industry is by forecasting the business trends using the appropriate technology that would assist the decision making process. This study explored the neural networks technology in analysing the historical customer requirements based on the teletraffic data that was produced from Telco peripherals. A ForecasTelco simulator was developed to experiment the capability of neural network technology in classifying the outputs. Several factors that contribute to the success of calls are determined. Five types of output are categorized ranging from not very successful to very successful. The simulator managed to generalize with 98% of accuracy.*

Keywords: telco, prepaid mobile, service control point, neural network, backpropagation

1. Introduction

Mobile telecommunication or Telco industry is considered as a competitive industry nowadays. New Straits Times in its Business Times section on Oct 13, 2003 has reported that Telco industries are competing with each others in serving the latest prepaid services to customer by introducing new packages, reducing call rates and other interesting packages. Celcom, Maxis, TmTouch, DiGi and TimeCel are among the Telco providers or carriers in Malaysia. There are many prepaid mobile Telco customers or known as subscribers around Malaysia and this number is increasingly rapidly.

In order to be sustained in Telco industries, the carriers need to plan their businesses as to ensure the increase use of their products and services. One of the strategies that can be applied in Telco industry is by forecasting their business trends such as analyzing historical customer requirements based on the teletraffic data that was produced from the Telco peripherals. Telco activities involve data collection about their customer and how do they use the networks, products and services (FileTek, 1999). The information is useful to the carriers to analyse the historical data and therefore focus on the target market segment.

This study focuses on the prepaid mobile business by looking at the performance of data or also known as call event records taken from local carrier at Celcom. Data is captured everyday from customer calls and usage, and call destination. The data is produced from many points in the chain of carrier server to make a call or connection that is categorized into successful and unsuccessful.

2. Business prepaid mobile

Lucent Technologies (1998) defined prepaid service as a service that enables customer to pay in advance for their call and other service features. This frees the customer from the inconvenience of handling regular bills or signing a contract. As a result customer's cash flow is optimised and fraud is minimised. A mobile prepaid application typically resides in either a service node or Service Control Point (SCP). The SCP represents the counters of callers in hour for everyday. Meanwhile, the overall functions and systems level interactions will vary according to which type of node and architecture that was deployed.

For the prepaid services, each mobile Telco carriers collect call event records from every call or connection of their prepaid mobile services monthly. Call event records may include switched, IP, wireless and other records relating to network transmission. These data assets are historical records that can tell the carriers what are the customer needs, how do they want to buy the services, who is unhappy, and who is profitable. Call event records give the ability to provide messaging between mobile switching

systems and prepaid systems for purposes of call control and administration. In more advanced or robust solution, call event records consists of common channel signalling system such as SS7 or C7 that provide the internetworking element messaging necessary for Intelligent Network (IN) call control.

Celcom prepaid services, collect teletraffic data or call event records from every call or connection of their prepaid mobile services monthly. Currently, Celcom manually used Lotus 123 and Ms Excel to create their teletraffic report in a monthly basis once data is collected from servers or connection points. The same datasets are been used in this study. The advantage of forecasting the SCP data by means of connectionist model or neural network is due to the accuracy produced through its short-term forecasting. This is useful for Celcom in assisting and improving their business planning.

3. Artificial Neural Networks

Neural networks are capable of learning and represents a class of very powerful, general-purpose tools that have been successfully applied to prediction, classification, and clustering problems. Some of forecasting applications that employ the ability of neural networks are forecasting regional load power (Hsu and Chen, 2002), sales (Luxhoj *et al.*, 1996; Kuo, 2001), GDP growth in Canada (Tkacz, 2001), exchange rates (Leung *et al.*, 2000), and ocean wave heights (Deo and Naidu, 1999).

It consists of a number of neurons that are connected by links, and each link has a numerical weight associated with it. The weights represent the strength or importance of each neuron input and neural networks learn through repeated adjustments of these weights. This study employs a multilayer perceptron model using backpropagation algorithm. The algorithm mainly consists of three stages, which are feed forward the input patterns, compute and back propagate the errors and finally updating the weights (Fausett, 1994). The algorithm is as Figure 1. The binary sigmoid function is used for the activation function both in hidden and output layers.

Step 1.0: Initialize weights

(Set to small random values between 0 to 1 or 0.5 to -0.5)

Step 2.0: While Stopping Condition is False, do
step 3.0 to 10.0**Step 3.0: For each training pair, do step 4.0 and 9.0****Feed Forward Input Pattern****Step 4.0:** Each input unit ($X_i, i = 1, \dots, n$) receives input signal X_i and broadcasts this signal to all units in hidden layer.**Step 5.0:** Calculate input signals to each hidden unit

$$z_in_j = v_{oj} + \sum_{i=1}^n x_i v_{ij}$$

Step 5.1: Activation function is applied to compute its output signal

$$Z_j = f(z_in_j)$$

Then the signal is sent to all units in output layer

Step 6.0: Each output unit ($y_k, k = 1, \dots, m$) sums its weighted input signals.

$$y_in_k = w_{ok} + \sum_{j=1}^p z_j w_{jk}$$

Step 6.1: Apply activation function to compute its output signal.

$$Y_k = f(y_in_k)$$

Back Propagation of Error**Step 7.0 :** Each output unit ($y_k, k = 1, \dots, m$) receives a target pattern correspond to the input training pattern, computes its error information term.

$$\delta_k = (t_k - y_k) f^1(y_in_k)$$

FIGURE 1. BACKPROPAGATION ALGORITHMS**ANN Parameters**

An optimum values of number of hidden nodes, momentum and learning rate determine the convergence process in backpropagation learning. Thus, these parameters are experimented in the training and testing process. Both learning rate and momentum are varied in the range of 0.1 and 1.0 while number of hidden is varied between 2 – 30. Number of epoch is experimented in the range of 100 – 10000. In each parameter, the highest two will be selected and experimented again by ranging the values of seed from 0.1 to 1.0. Nguyen-Widrow and random techniques are used in initializing the weights. Training was stopped when the stopping criteria is achieved. The stopping criterion is based on number of epoch or mean square error ≤ 0.005 whichever condition satisfied first.

Data Collection and Preprocessing

The raw data has been collected via different servers and labelled as SCP1, SCP2, SCP3, SCP4 and SCP5. Data was selected randomly in a daily basis between 8:00 pm and 9:00 pm (Paungma *et al.*, 2001). This is considered the busy hour of a peak day and the optimum processing time made by users everyday. The raw data was taken for three consecutive months starting from 1st July 2003 to 30th

September 2003 excluding the day of server maintenance and upgrade. According to Delurgio (1998), this period can be classified as a short term forecasting.

Several techniques of preprocessing involved. For discrete data, such as SCP is mapped on the interval from 0 to 1 as shown below:

SCP1 = 0.2 SCP4 = 0.8
SCP2 = 0.4 SCP5 = 1.0
SCP3 = 0.6

For continuous data, such as date, the linear scaling is used. The formula is as below:

$$x_{new} = \frac{x_{old}}{365}$$

or

$$x_{new} = \frac{x_{old} - x_{min}}{x_{max} - x_{min}}$$

where x_{new} and x_{old} represent a new and an old input value respectively. x_{min} and x_{max} represent a minimum and a maximum values of the selected item respectively.

The output was preprocessed using 1 of N coding (Berry and Linoff, 1997). In this study, the success call is based on $urc_dbsc(x)$. Before the variable is categorized in the following form, it was preprocessed using the mentioned preprocessed method.

Condition of $urc_dbsc(x)$	Binary representation	Representation description
If $x > 0.9$	[0,0,0,0,1]	<i>not very successful</i>
If $0.7 < x \leq 0.9$	[0,0,0,1,0]	<i>not successful</i>
If $0.5 < x \leq 0.7$	[0,0,1,0,0]	<i>moderate successful</i>
If $0.3 < x \leq 0.5$	[0,1,0,0,0]	<i>successful</i>
If $x \leq 0.3$	[1,0,0,0,0]	<i>very successful.</i>

4. Results and Discussion

There are 368 data sets used in training and 46 data sets used for testing. The selection of optimum values is based on the highest generalization produced in the test data sets that was not used in training the network. The optimum values of learning rate (α), momentum (μ), hidden unit and epochs are found to be 0.5, 0.5, 20 and 1200.

Therefore, the proposed model or ForecasTelco is 5 – 20 – 5 that represent the number of inputs, hidden nodes and number of outputs. The five inputs are SCP, Date, Day1, Day2, Day3.

Table 1, 2, 3, 4 shows the simulation results for different values of hidden unit, momentum, learning rate, and number of epochs respectively. ForecasTelco is able to generalize training and testing data into 98.1% and 98.9% respectively. Figure 2 illustrates the main interface of ForecasTelco.

TABLE 1. SIMULATION RESULTS FOR DIFFERENT HIDDEN UNITS

HU	TRAINING	TESTING
2	86.68	80.43
4	89.40	90.22
6	91.03	91.30
8	91.58	93.48
10	90.49	91.30
12	93.21	93.48
14	91.30	92.39
16	92.66	92.39
18	91.30	90.22
20	92.93	94.57
22	92.93	92.39
24	91.03	93.48
26	91.58	93.48
28	92.39	93.48
30	93.21	93.48

TABLE 2. SIMULATION RESULTS FOR DIFFERENT LEARNING RATES

α	TRAINING	TESTING
0.1	91.30	82.61
0.2	94.29	90.22
0.3	91.58	92.39
0.4	93.75	91.30
0.5	92.93	94.57
0.6	93.48	93.48
0.7	94.02	91.30
0.8	93.75	90.22
0.9	90.22	89.13
1.0	91.30	91.30

TABLE 3. SIMULATION RESULTS FOR DIFFERENT MOMENTUMS

μ	TRAINING	TESTING
0.1	93.75	92.39
0.2	93.48	92.39
0.3	94.29	94.57
0.4	91.58	91.30
0.5	92.93	94.57
0.6	92.93	92.39
0.7	91.30	90.22
0.8	94.57	91.30
0.9	91.30	86.96
1.0	54.89	56.52

TABLE 4. SIMULATION RESULTS FOR DIFFERENT EPOCHS

EPOCH	TRAINING	TESTING
100	92.93	94.57
300	95.38	95.65
500	95.65	93.48
700	97.01	94.57
900	97.55	97.83
1000	97.83	96.74
1200	98.10	98.91
1400	97.83	96.74
1600	98.10	95.65
1800	98.10	97.83
2000	98.10	97.83
2500	98.37	97.83
3000	98.10	97.83
3500	98.64	98.91
4000	98.10	98.91
4500	98.37	97.83
5000	98.10	98.91
5500	98.10	97.83
10000	98.37	98.91

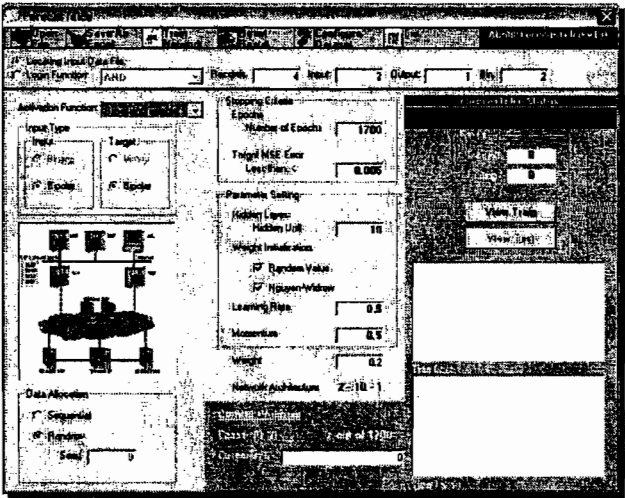


FIGURE 2. FORECASTELCO MAIN INTERFACE

5. Conclusion

The results indicate that neural network technology can be a tool in forecasting business prepaid mobile communication. The performance of the developed model with the accuracy above 98 percent is satisfactory. The developed connectionist model simulator, *ForecasTelco* using the back propagation algorithm has demonstrated its ability in training the given input and output patterns. *ForecasTelco* is able to capture data from the call event records towards forecasting the trends of business prepaid mobile Telco. It is hope that ForecasTelco simulator would assist the decision makers towards forecasting their business trends and taking suitable strategies for competing in Telco industries.

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