Predicting TV Audience Rating with Social Media

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Abstract

In Taiwan, there are different types of TV programs, and each program usually has its broadcast length and frequency. We accumulate the broadcasted TV programs' word-of-mouth on Facebook and apply the Back-propagation Network to predict the latest program audience rating. TV audience rating is an important indicator regarding the popularity of programs and it is also a factor to influence the revenue of broadcast stations via advertisements. Currently, the present media environments are drastically changing our media consumption patterns. We can watch TV programs on YouTube regardless location and timing. In this paper, we develop a model for predicting TV audience rating. We also present the audience rating trend analysis on demo system which is used to describe the relation between predictive audience rating and Nielsen TV rating.

1 Introduction

As social media websites develop, more and more people are sharing their thoughts on these types of websites (such as Facebook). Many enterprises noticed this trend, and started creating fan pages on Facebook to interact with the customers in order to create a simple channel for interaction to consolidate customer loyalty. Currently, many television companies have creates fan pages for shows that they are broadcasting, and use the role of editor to announce upcoming plots or actor information to interact with the viewers and get responses from them, in order to try to increase ratings; higher rates help bring in more advertising revenues for the television company.

Because these types of social media websites, such as Facebook, have already become a part of people's everyday life, this research will try to use the contents generated in the TV program fan pages by viewers and the editor (including Posts, Likes and Comments etc.) and the Artificial Neural Network to perform forecasts on program ratings. If television companies can find out ratings information in advance, they can use this as a basis to negotiate the advertising period and fees with advertisers; it can also help the television channel observe the benefits of operating program fan pages, and then decide whether to reinforce fan page management or add additional interactions with the fans and further increase ratings and profits.

This research constructed a program ratings forecast module based on Back-propagation Network. This model uses various information on fan pages of completed broadcasting programs and the actual ratings to perform the training for the Artificial Neural Network, and then uses the trained Artificial Neural network to perform a ratings forecast for upcoming programs.

2 Preliminary

2.1 Artificial Neural Network

The Artificial Neural Network uses a large number of simple artificial neurons that mimics the biological neural network's processing, transmitted and learning process and abilities in order to implement the biological neural network's information processing system. The architecture of a common 3-layered neural network is shown in the figure below:

1

Input Layer   Hidden Layer   Output Layer

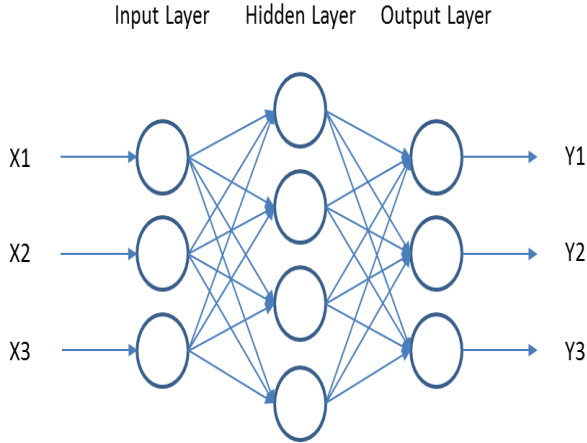X1 →   → Y1

X2 →   → Y2

X3 →   → Y3

Figure 1. 3-layered neural network

The Back-propagation Network used in this research is a supervised learning network. It uses the error that each epoch generated during training, and adjusts each neuron's weight using a gradient descent to minimize training errors to adapt to the data of the training data set, and apply the unseen data to the trained network to perform a forecast. The correction method of Error is as follows:

$$w_{k+1} = w_k - \eta \sum_{t=1}^{k} \alpha^{k-t} \left(\frac{\partial \varepsilon_t}{\partial w_t} \right) \qquad (1)$$

In which ε is the sum of the accumulated errors of each epoch, η is the learning rate, and in order to make the update of w more gentle and avoid oscillation, that is why α (momentum) is quoted to accelerate convergence.

Currently, many researchers has used the back-propagation method to train their network to perform forecasts; Ismail and Jamaluddin uses BPN to perform forecast to the electricity load demand, and the result showed that when Sigmoid is used as the activation function, the forecast data was closer to the actual data. Baboo and Shereef also used 3-layered back-propagation neural network to perform weather forecasts, and the result also showed that BPN has excellent generalization capacity.

2.2   Social Network

Although Facebook has been very popular as a web service, there has not been considerable published research on it. Huberman and others [2] studied the social interactions on Twitter to reveal that the driving process for usage is a sparse hidden network underlying the friends and followers, while most of the links represent meaningless interactions. Java et al [1] investigated community structure and isolated different types of user intentions on Twitter. Jansen and others have examined Twitter as a mechanism for word-of-mouth advertising, and considered articular brands and products while examining the structure of the postings and the change in sentiments. However the authors do not perform any analysis on the predictive aspect of Twitter.

3   Training Model

The sources of the data used in this research are the number of posts, likes, comments and shares etc. of each post in the various program fan pages, and the counts of these from the fan page administrators and fans were calculated separately. The data from a total of 4 fan pages were used (Office Girls, Love Forward, The Fierce Wife, and King Flower, in which King Flower is a program that is still currently airing); the ratings data of historic programs were provided by the television companies.

This research mainly focuses on a TV drama that airs once a week, and collects the number of discussions on the fan page every week and the corresponding ratings for the episode aired each week to use as the training and test data; the data includes 10 properties: #Page Posts, #Page posts comments, #Page posts likes, #page posts shares, #Fans posts, #Fans posts comments, #Fans posts likes, #Fans posts shares, previous episode TVR, and 1st episode TVR. In which, the number of comments is the number of unrepeated response count for each post, used to lower the effects on the forecast results caused by vast responses due to special events. In order for the data to be able to be used by the Back-propagation Network back-propagation, all the data were normalized before training and testing so that they are between 0 and 1, and then the data were inputted to perform training or testing. In order to acquire the 1st episode TVR, forecast was not performed for the ratings of the first episode.

In consideration of the duration of the plot being discussed in to fan page, this research used a sliding window to integrate the data to create sums of data accumulated within 3 weeks and 1 week to use as the input data.

D. Meyer & R. J. Hyndman's recommendation was used for the percentage value of TVR, and Arcsine transformation was performed to prevent heteroscedasticity from happening.

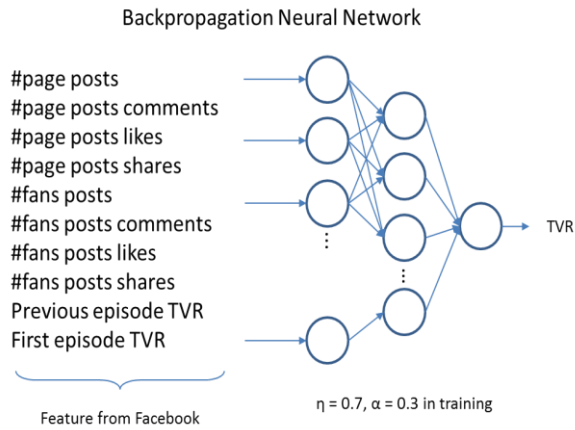The architecture of the neural network is as shown in the figure below:

Figure 2. Training Model

4　Experiments

This research used the Cross Validation method to perform experiments. Four out of five programs were picked out every time to use as training data; 70% of the training data is used for training and 30% is used for testing. Finally, the fan page data from the last program was used to perform forecast for the ratings of every episode of the program, then use mean absolute error (MAE) and mean absolute percentage error (MAPE) to compare and evaluate the forecast model.

For learning rate (η), momentum (α) and error tolerance (τ), it was discovered after the experiment that when η=0.7,α=0.3 and　τ=0.06, the forecast performance was most ideal.

The number of episodes and ratings of each program are shown in the table below:

Drama Name	#Episode	Max TVR (%)	Min TVR (%)
Office Girls	25	7.33	2.78
Love Forward	22	2.67	1.97
The Fierce Wife	23	9.80	0.91
King Flower	8	2.14	1.29

Table 1. Episode of each program

The forecast results of each program were measured with its Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE); the results are shown as in the table below (the accumulation of one week is abbreviated as C1 and the accumulation of three weeks is abbreviated as C3):

Drama Name	MAE (C1/C3)	MAPE (C1/C3)
Office Girls	0.2946 / 0.5115	5.73% / 10.47%
Love Forward	0.1775 / 0.2042	7.59% / 8.99%

The Fierce Wife	0.4090 / 0.4861	11.37% / 23.71%
King Flower	0.1969 / 0.1959	11.19% / 17.10%

Table 2. Episode of each program

MAPE(%)	Evaluation
MAPE ≤ 10%	High Accuracy Forecasting
10% ≤ MAPE ≤ 20%	Good Forecasting
20% ≤ MAPE ≤ 50%	Reasonable Forecasting
MAPE > 50%	Inaccurate Forecasting

Table 3. Lewis' MAPE definition

From the table above it can be seen that the performance of the value data of the accumulation of one week is better than the accumulation of three weeks; and according to Lewis' (1982) definition of the MAPE value, the performance of the value data of the accumulation of one week are all between the high accuracy forecasting and good forecasting. This shows that using the various data from fan pages to perform future ratings forecasts is feasible. The forecast table of each program is shown in the figures below:
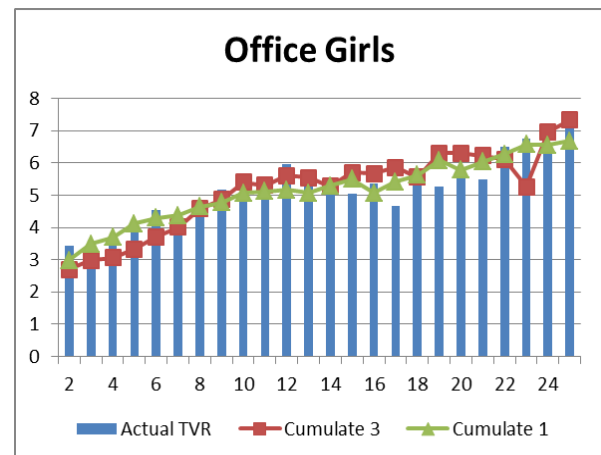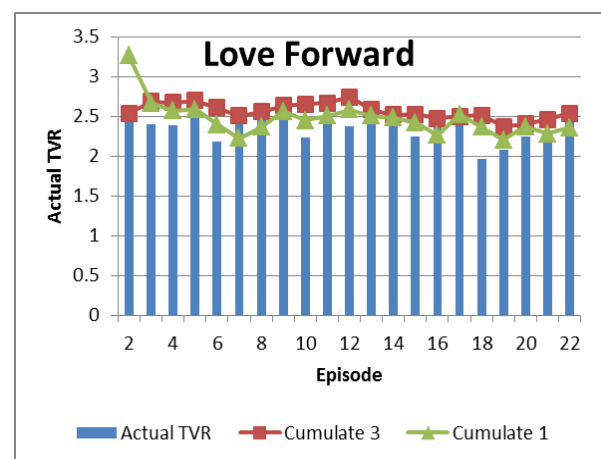

Figure 3. Rating forecast of Office Girls

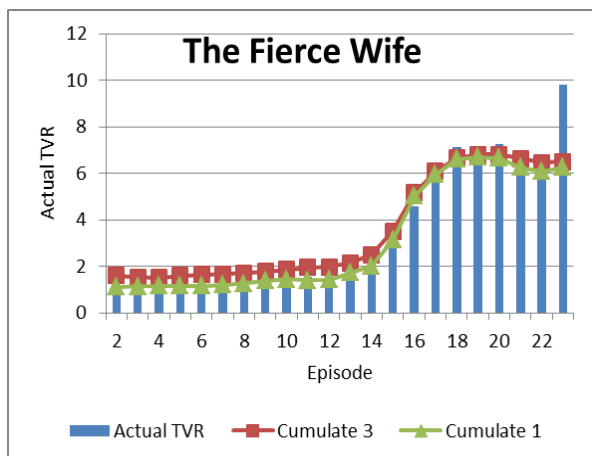Figure 4. Rating forecast of Love Forward

3

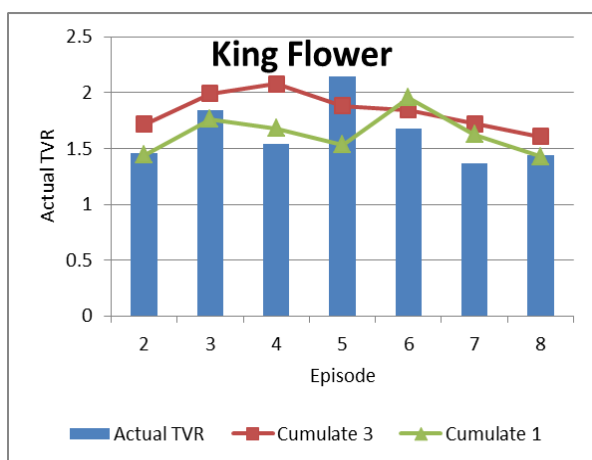Figure 5. Rating forecast of The Fierce Wife

Figure 6. Rating forecast of King Flower

From the various figures above and the performance of the MAPE value, it can be seen that the results from using the Back-propagation Network back-propagation to perform forecasting matches the actual ratings in most cases, in which performance was optimal when the accumulated data of one week was used to perform the training and testing; only two sets fell between the good forecasting interval, and the rest all fell between the high accuracy forecasting interval.

5   Discussion

We also discovered some problems during the experiment process. For example, in episode 17 of Office Girls, episode 2 of Love Forward and episode 4 of King Flower, the ratings were obviously overrated; in which Office Girls and King Flower were each affected by the premiere and finale of other programs from other television companies, therefore, viewership was divided. In the future, if television companies can take the

initiative to provide the current status and special events (premiere and finale) of program broadcast from other television channels, this should be able to lower this type of error. As for Love Forward, the fan page administrators posted articles such as "If you like it, then press Like/Share", resulting in the number of Likes and Shares to vastly increase and further cause the ratings to be overrated. Therefore, in the future, keyword detection for the content of these types of articles is necessary to lower the effects caused by these large amounts of Likes and Shares. In addition, the ratings of episodes 21 and 22 of Miss Rose suddenly dropped without facing premieres or finales of other programs or special events; therefore, in-depth probing for the various elements which affected their ratings is needed.

6   Conclusion

This research used the back-propagation Network and the number of posts, likes, comments and shares on the fan pages of various TV dramas to try to find their relationships to ratings. First of all, the various data information from the fan pages of 4 TV dramas were collected, and the number of repeated respondents in the same article was filtered out in order to avoid large amount of increased responses due to special events (such as quizzes or Facebook Meeting Rooms etc.) from affecting the forecast of ratings. Because the discussion of plots will not centered in one day, the sliding window method was used to generate the experiment data sets, and were divided into two data sets: the accumulation of the previous week and the accumulation of the previous three weeks. Then the data were normalized and the cross validation method was used to perform forecast module training and testing for every program. The result showed that using Facebook fan page data to perform ratings forecasts for unaired programs should be feasible.

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