https://doi.org/10.48009/2_iis_2008_300-304

TOPIC INFLUENCES ON ELECTRONIC MEETING RELEVANT COMMENTS

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ABSTRACT

Only rarely have researchers attempted to mathematically model the complex interrelationships of variables within an electronic meeting. Here, we show how topic-related measures can be used by an artificial neural network to accurately forecast the number of relevant comments generated by each person in these automated meetings. In comparison, naïve and multi-linear regression forecasts were significantly different from the actual numbers of comments.

Keywords: Electronic Meetings, Group Decision Support Systems (GDSS), Artificial Neural Networks

INTRODUCTION

Groups using electronic meeting systems (EMS) – otherwise known as group support systems (GSS) or group decision support systems (GDSS) - have been studied for over 20 years [17], and most research has shown that electronic meetings are superior to traditional, oral meetings when the group size is greater than seven and all individuals need to contribute, as in a brainstorming session [21]. In a typical meeting using an EMS, group members exchange typed comments about a proposed topic anonymously in a face-to-face environment [10, 24]. Because anonymity is provided, there is less evaluation apprehension (fear of others' criticism) in these meetings, and because all members can type and read comments simultaneously, there is more participation. Because there is less evaluation apprehension and more participation, groups using an EMS often generate more comments during the session and are more satisfied [13].

However, many interrelated variables can influence meeting satisfaction and the number of comments produced, including individual typing and reading speeds, the specific idea generation technique used, and the specific task or topic of the meeting [12, 22]. The purpose of this paper is to investigate how the choice of meeting topic can affect the number of relevant comments produced by each member of the group.

MODELLING ELECTRONIC MEETINGS

Some attempts have been made to model the interrelationships among electronic meeting variables mathematically. For example, one study used a linear equation to show how the number of comments generated in an EMS meeting varies with group size [25], and another demonstrated through formulas the costs and benefits of electronic meetings [6]. A third study [7] provided mathematical models of idea processing and generating rates, optimum group sizes, and time savings.

But, few researchers have attempted to use these models to actually forecast meeting outcomes such as process satisfaction or the number of comments generated by the group [26]. Perhaps part of the reason is that most statistical techniques cannot adequately accommodate the complex, interrelated nature of the variables in the meeting. Artificial neural networks (ANNs), otherwise known as artificial neural systems (ANSs) or simply neural networks (NNs), can provide the solution to this forecasting problem, as they can model non-linear relationships among variables and are more accurate than competing statistical forecasting techniques such as Logit and Probit [14]. Yet, neural networks are still relatively rarely used in the realm of GSS research because of a lack of awareness of the technique, a lack of access to the software, or a lack of knowledge of how to use the programs.

A few studies have shown how neural networks can accurate forecast variables within electronic meetings, however. For example, a neural network classified participants as being within an electronic meeting or verbal meeting with 90% accuracy (versus 76% accuracy using linear regression) based upon their responses on evaluation apprehension, satisfaction, and extent of participation [1]. In another study, a neural network predicted the length of the meetings based upon knowledge of the topic, complexity of the problem, and experience with the software with 76% accuracy [3].

Using a similar technique called logical abduction, one study [5] showed that researchers were able to forecast meeting process satisfaction using only group size and

idea generation technique with a mean absolute percentage error (MAPE) of 8.77% versus an MAPE of 44.52% with a multi-linear regression model. Using comment generation rate, production blocking, and evaluation apprehension variables, researchers were able to predict meeting process satisfaction with an MAPE of only 6.54%.

TOPIC EFFECTS IN ELECTRONIC MEETINGS

Many different topics have been used in prior studies of meetings, including:

- What are the advantages and disadvantages of having two thumbs on each hand? [2].
- "How high does the chance of later employment have to be before you would advise a fellow student to join a very desirable trainee program prior to finishing the undergraduate thesis?" [11].
- "How can we solve the parking problem on campus?" [19].
- "Should tuition be raised?" [2].
- "How could you safely change a tire on a busy expressway at night?" [16].
- "How can the spread of AIDS be reduced?" [23].
- "What makes for success in our culture?" [
- "How can we encourage more tourists to visit the city?" [23].
- "What type of soft drink should be in the vending machines on campus?" [2].

With each of these topics, individual group members had varying degrees of knowledge about, interest in, and ability to influence the subject. But if a topic is boring, or the group members have little knowledge of the subject or control over the solution of the problem, they may be more likely to switch spontaneously to another topic to pass the time [9]. For example, if a group of undergraduate business students in an electronic meeting is asked to propose new procedures for brain surgery, they are not likely to type many relevant, on-topic comments, but instead, might start to exchange comments about sports, politics, or something else more interesting to them.

In most brainstorming meetings, the goal is to maximize the size of the knowledge space of potential solutions to a problem. Thus, it is the number of relevant comments that is most important, not the total number. While no group is likely to be faced with such a mismatched problem as business students discussing brain surgery, each participant in a meeting naturally has different levels of understanding, interest, and control that influence his or her ability to generate quality ideas. However, no prior research has attempted to model this individual behavior and forecast the number of relevant comments based solely on their feelings about the meeting topic.

EXPERIMENTAL STUDY

An experiment was conducted using 108 Business students, aged 20 to 46. The subjects were assigned randomly to 14 groups, each with seven to eight participants because this is the minimum size needed for electronic meeting [4]. Each group was randomly assigned one of five topics to discuss using electronic meeting software implementing the gallery writing technique that allowed each participant to post and view comments anonymously and simultaneously in a face-to-face environment [8].

After 10 minutes exchanging typed comments, group members completed a short questionnaire assessing their opinions about their knowledge, interest, and ability to control the topic using a scale ranging from 1-strongly disagree to 7-strongly agree. In addition, objective evaluators determined the number of relevant comments (that is, the comment had something to do with the topic) generated by each participant. Summary results are shown in Table 1.

Table 1: Questionnaire Summary Results

Variable	Description	Mean	Std Dev
rel	Number of relevant comments	6.093	3.909
Q1	Topic has more than one solution	5.574	1.542
Q2	Subject has knowledge of the topic	3.685*	1.678
Q3	Topic is meaningful	5.204	1.898
Q4	Topic is involving	5.213	1.635
Q5	Topic is attractive	4.630	1.780
Q6	Topic is interesting	5.074	1.667
Q7	Topic is unclear	2.852	1.679
Q8	Subject can influence others about this topic	4.454	1.620
Q9	Topic is difficult	3.509	1.931

* = not significantly different from questionnaire "neutral" value of 4 at $\alpha = 0.05$

Table 2 shows that all of the variables were significantly correlated with the number of relevant comments generated by each group member. Therefore, using these variables, it might be possible to accurately forecast the number of comments with a neural network.

Table 2: Topic Variable Correlations with Relevant Comments

Variable	R	p-value
Q1	0.377	< 0.001
Q2	0.393	< 0.001
Q3	0.247	0.010
Q4	0.288	0.003
Q5	0.545	< 0.001
Q6	0.545	< 0.001
Q7	-0.320	< 0.001
Q8	0.232	0.012
Q9	-0.369	< 0.001

FORECASTING RELEVANT COMMENTS

We used *Neuroforecaster 3.1* with a genetic training algorithm to model the data obtained in the experiment. The first decision to be made was the determination of the in-sample (training) and out-of-sample (testing) data sets. The training set should be large enough for the neural network to adequately train on a large representation of possible inputs, but some data must be left for the testing data set. One tool provided by the software that aids with this subjective decision is the Indicator Distribution Pattern Window [20]. The goal using this tool is to cover as many quadrants as possible in the window, thus exposing the software to many possible problem scenarios. As the training sample size is increased, in general, more quadrants are covered. The nine input variable distribution pattern windows represent a training set size of 88, leaving 20 observations for testing. We subjectively decided this sample size was large enough.

Another subjective decision is when to stop training. Figure 1 shows the neural network after 1.3 million iterations with the in-sample MAPE reduced to about 19%.

Because the in-sample MAPE was not declining much further at this point, we tested the neural network forecasts with the 20 out-of-sample observations (see Figure 2) and obtained an MAPE of 21%, slightly higher than the in-sample MAPE, which is normal.

Figure 1: Neural Network Training

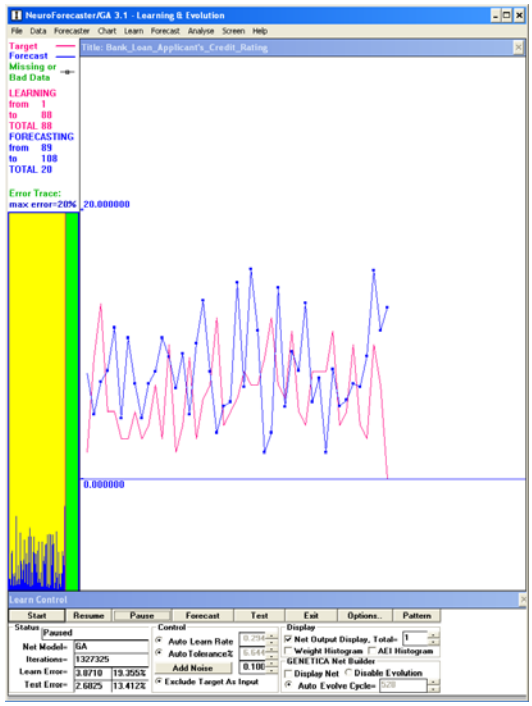
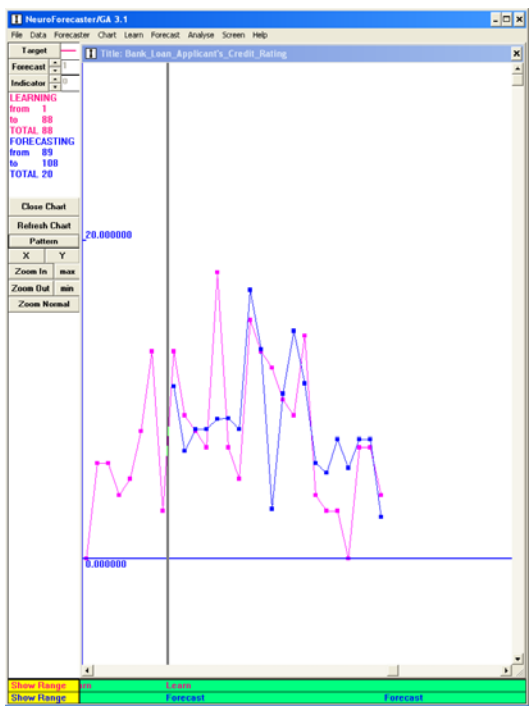


Figure 2: Neural Network Testing



For a comparison, we also conducted a naïve forecast in which the number of relevant comments per individual in the testing set is forecasted to be the same as the average number of relevant comments for all individuals in the training set. This forecast resulted in an MAPE of about 43%. Finally, a multi-linear regression forecast was conducted using the SAS General Linear Model (GLM) procedure ($F = 8.62$, $p < 0.001$), resulting in an MAPE of about 31% for the testing set. Results for all three forecasting techniques are summarized in Table 3.

Table 3: Neural Network, Naïve, and Regression Testing Results

Actual	NN	APE %	naïve	APE %	Regression	APE %
13	13.6	4.62	5.56	57.23	7.26	44.13
9	8.3	7.78	5.56	38.22	4.74	47.29
8	7.2	10.00	5.56	30.50	6.36	20.47
7	8.7	24.29	5.56	20.57	7.46	6.50
18	10.1	43.89	5.56	69.11	8.81	51.05
7	8.1	15.71	5.56	20.57	7.63	8.99
5	5.5	10.00	5.56	11.20	4.20	16.00
15	15	0.00	5.56	62.93	5.97	60.18
13	12.2	6.15	5.56	57.23	6.87	47.18
12	3.6	70.00	5.56	53.67	6.20	48.36
10	8.3	17.00	5.56	44.40	7.55	24.47
9	14.8	64.44	5.56	38.22	4.88	45.74
14	11.5	17.86	5.56	60.29	9.68	30.87
4	4.1	2.50	5.56	39.00	5.39	34.87
3	3.8	26.67	5.56	85.33	3.65	21.59
3	4.9	63.33	5.56	85.33	3.76	25.37
0	5.1	0.00*	5.56	0.00*	2.81	0.00*
7	7	0.00	5.56	20.57	8.78	25.45
7	7.5	7.14	5.56	20.57	8.55	22.08
4	2.7	32.50	5.56	39.00	2.80	30.00
Averages						
8.4	8.1	21.19	5.56	42.70	6.17	30.56

* = Absolute Percentage Error (APE) cannot be calculated when the divisor is not positive. Instead, a 0 was substituted as the error for this observation.

A difference of means t-test showed that there was no significant difference between the neural network estimates and the actual numbers of relevant comments per meeting participant ($t = -0.40$, $p = 0.693$), but there were significant differences between the naïve estimates ($t = -2.72$, $p = 0.013$) and the linear regression estimates ($t = -2.74$, $p = 0.013$) and the numbers of relevant comments. Thus, the neural network was more accurate than these two alternative forecasting techniques.

CONCLUSION

In determining the topic for a discussion, group leaders might want to know before-hand whether or not the problem is appropriate and whether or not the meeting will be a success, as determined, for example, by the number of relevant comments that will ultimately be generated. Using a neural network, a relatively accurate forecast of the numbers of comments generated by each group member can be made based upon the self-assessed interest in and knowledge of the topic and the perceived solution multiplicity and difficulty. Improvements in forecasting accuracy might be obtained using additional variables such as measures of individual typing speed and willingness to contribute to conversations. Future research should investigate the affect of these variables and select a broader range of discussion topics.

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