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Title: A Methodology to Predict Specific Communication Themes from Overall Communication Volume for Individuals and Teams

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Authors:

Elliot E. Entin
Aptima Inc.,
12 Gill Street, Suite 1400
Woburn, MA 01801
Phone: 781-496-2438
Fax: 781-935-4385
e-mail: entin@aptima.com

Shawn Weil
Aptima Inc.,
12 Gill Street, Suite 1400
Woburn, MA 01801
Phone: 781-496-2456
Fax: 781-935-4385
e-mail: sweil@aptima.com

Correspondence:

Elliot E. Entin
Aptima Inc.,
12 Gill Street, Suite 1400
Woburn, MA 01801
Phone: 781-496-2438
Fax: 781-935-4385
e-mail: entin@aptima.com

A Methodology to Predict Specific Communication Themes from Overall Communication Volume for Individuals and Teams

Elliot E. Entin
Aptima Inc.

Shawn Weil
Aptima Inc.

Abstract

We focus on a means to code voice communications and derive communication measures because communication plays such a critical role in military decision making and mission accomplishment. Voice communication has proved labor intensive to code manually and, beyond simple counts of utterances, has proved relatively intractable to automate coding even for powerful computers. The methodology we describe has the potential to alleviate a significant portion of the current coding burden. It only assumes there is a technology to count the number of utterances per trial. The process involves randomly selecting a subsample from a larger data set, manually coding the subsample using standard manual coding procedures to produce a small set of communication measures, constructing regression models using corrected part-whole correlations to predict each communication measure from the number of utterances, and applying the models to predict communication measures for the remaining part of the data set. This methodology was tested using data from a recent study. Results revealed acceptable corrected part-whole correlations and subsequent regression models. Moreover, predicted communication scores from the subsample based regression models showed similar communication patterns found for scores derived from the whole sample. Implications of these finds are discussed.

Introduction

We focus on communications in this paper because organizations and teams typically coordinate actions such as the reallocation of assets, the redistribution of workload, and joint processing of tasks via voice communication (Orasanu, 1990; Entin & Serfaty, 1999). Moreover, the major conduit for the sharing of information and identifying the need for change is typically voice communication (Diedrich, et al., 2003). MacMillan, et al. (2005) highlight the importance of explicit communication to achieve the necessary sharing of information among team members so that organizations and teams can act in concert to achieve common goals. In a study to identify the conditions that cause organizations to alter their current organizational structures, Entin, et al. (2003a) identified several measures of communication that signal to members of an organization that a change in organizational structure may be necessary. In a related paper, Entin, et al. (2003b) discuss results indicating that communications increased when teams were faced with a situation in which the organizational structure they were using was no longer appropriate for the mission to be accomplished. Beyond overall communication rate, however, there were also important differences in communication patterns (e.g., who talked about what).

Given the criticality of communication to the understanding of organization and team performance, it is not surprising that various protocols to code and analyze communications have been devised (see Orasanu, 1990; Entin and Entin, 2001). However, the process of coding team communications to derive communication measures such as those described by Entin and Entin (2001), are not without constraints.

When communications among team members are captured at a detailed semantic level, it is both difficult and time consuming to develop meaningful, quantitatively-based measures to describe the nature of the communications. At the opposite end of the continuum, simple frequency counts of utterances, though straightforward, do not provide a meaningful window into team processes. Entin and Entin (2001) discuss an approach that permits verbal communications among the members of a team to be captured by observers at an *intermediate* level of detail that incorporates both semantic and quantitative aspects of the communication stream. A trained observer, using a handheld tablet or laptop computer running specifically designed software, codes the source, the recipient, the time, and the type of the verbal communications among the team members. In this approach types of communications are divided into three basic categories: transfers, requests, and acknowledgements. Both transfers and requests are, in turn, classified as requests for information, action, or coordination. This procedure has proved to be a useful and sensitive means to capture and code communications and help explain team behavior (Entin, 1999; Entin and Serfaty, 1999; Diedrich, et al., 2003). Although this procedure provides a good compromise between highly detailed verbal coding and the mere count of utterances it is still a fairly labor intensive procedure.

One would think that in these days of powerful computers and sophisticated software that automated methods exist to reliably code verbal communications, thus greatly reducing the labor intensity of communication coding. But to date we have not been able to locate software that is up to the task. Some developers argue that voice recognition applications are at hand to produce reliable counts of the number of utterances (communication volume) made by specific individuals during a scenario. Moreover, if voice-over-Internet Protocol is employed and used for recording relatively unsophisticated applications exist to provide an overall count of the number of utterances in a session. Assuming an automated tool can produce a measure of communication volume, could we come to know anything about the pattern of communication for the team doing the communicating? In other words, could we build a model or family of models that would allow us to predict some communication categories (measures) knowing only the volume of communication? We hypothesized that a model based on linear regression could do just that.

Method

Overview

The methodology to be described is relatively straight forward. Assuming that recordings were made of all trials, randomly select a 20% to 25% sample of trials from all trials conducted. Code the communications of the randomly select trials manually using some coding protocol like that described by Entin and Entin (2001) to arrive at counts for a small (e.g., three or four) but meaningful set of communication categories. Next, for each of the communication categories construct a linear regression model using total number of utterances (communication volume derived from a software application applied to derive the number of utterance per trial) per person or team as the independent (predictor) variable and a communication category as the dependent (to be predicted) variable. The resulting correlation between total number of utterances and a communication category is a part-whole correlation and, if uncorrected, will most likely yield an inflated correlation coefficient. Fortunately there are formulae that can be used to derive the uninflated correlation. An example of one such formula is given by Guilford (1965, p.350). It is the corrected part-whole correlation that is used to construct the regression model. The regression models derived for the sub-sample can now be applied to predict the communication categories in the remaining research sample.

Procedure

To test this method and assess its veracity we employed the 32 trials from the Diedrich et al. (2003) study. We selected four communication categories that were identified by several studies (Entin, et al., 2003b; Entin, 1999; Entin and Serfaty, 1999) as communication categories that indicate changes in the current organizational structure may be necessary or have demonstrated significant utility describing team performance and team dynamics. The selected four communication categories are: information requests, information transfers, coordination requests, and coordination transfers.

Using all 32 trials we computed the part-whole correlations for each of the chosen communication categories. We next corrected the part-whole correlations using the correction formula provided by Guilford (1965, p.350) to derive the uninflated part-whole correlations. Using the corrected part-whole correlations, a simple regression model was constructed for each of the selected communication categories. We started with analyses based on the whole sample to establish a baseline on how well part-whole correlations could predict each of the selected communication category scores. The procedure we are proposing, however, calls for a smaller randomly selected sample of the trials to construct the regression models. To assess the validity of this aspect of the methodology we selected a 25% random sample of the 32 trials, or eight trials. To select the eight trials randomly we used the random number generator in Excel to generate numbers between 1 and 32. Once the random sample was identified, we essentially duplicated the methodology described above for the whole sample. That is, corrected part-whole correlations were computed that were used to construct simple regression models for the four selected communication categories.

Results

Regression Models

A summary of the regression analyses based on the whole sample is presented in Table 1. As we can see, all the zero order correlations between the four communication categories and the total volume of communication are significant, all the regression models are significant, and the models account for between 20% to 45% of the variance. In addition, inspections of the residuals revealed no significant outliers or influential data points.

Table 1 Summary of Regression Analyses Performed on Entire Sample

Communication Categories	Mean	Std. Dev.	N	Correlation	Adjusted Correlation	R Square	b	a	Regression F
Information requests	9.44	10.68	32	0.48*	0.44*	0.20	0.05*	-5.80	8.60*
Information transfers	30.94	22.95	32	0.53*	0.45*	0.20	0.11*	-2.00	11.51*
Coordination requests	17.44	12.31	32	0.71*	0.68*	0.46	0.09*	-9.41	29.12*
Coordination transfers	14.75	11.35	32	0.69*	0.66*	0.43	0.08*	-9.28	26.24*

* Significant $p < .01$

Table 2 shows a summary of the regression analyses based on the 25% random sample. In all instances the correlations derived from the random 25% sample were somewhat larger than that seen for those categories derived from the whole sample, but with the reduced sample size only three out of four of the correlations proved significantly different from zero at the 5% level. The R squares for the 25% random sample varied between .42 and .68 and three out of the four regression models were significant. An examination of the residuals revealed only one significant outlier for information request; all else appear nominal.

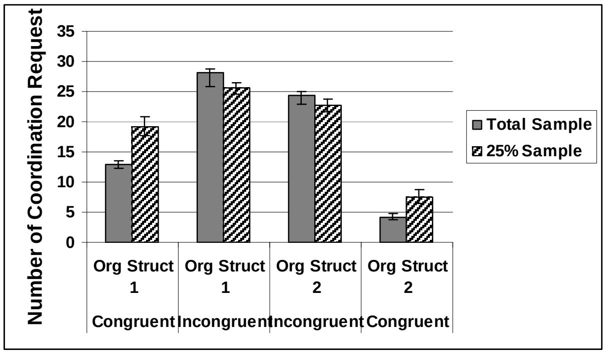
Table 2 Summary of Regression Analyses Performed for the 25% Sample

Communication Categories	Mean	Std. Dev.	N	Correlation	Adjusted correlation	R Square	b	a	Regression F
Information requests	**8.63**	**14.40**	**8**	**0.69**	**0.65**	**0.42**	**0.09**	**-14.50**	**4.99**
Information transfers	**24.13**	**29.50**	**8**	**0.78***	**0.70***	**0.48**	**0.20***	**-26.53**	**9.01***
Coordination requests	**14.38**	**12.76**	**8**	**0.84***	**0.82***	**0.68**	**0.10***	**-11.55**	**13.90***
Coordination transfers	**10.88**	**9.63**	**8**	**0.79***	**0.77***	**0.59**	**0.07***	**-7.41**	**9.10***

* Significant $p < .05$

Examining Patterns of Communications Results

The goal of the methodology described is to produce communications scores that are comparable to scores derived from traditional methods (i.e., coding the whole sample) while expending less time and effort. But, if the scores derived from the new methodology do not adequately represent the traditionally derived scores, the new method is not worth much. To gauge the utility of the communication scores produced from the new method we tested to see if they produced the same pattern of results described by Entin et al. (2003a) for the traditional scores. The model driving the Entin et al. (2003a) study predicts that when the organizational structure used by a team fits or is congruent with the mission to be performed communication overhead in terms of volume and particularly coordination requests and transfers will be lower than when the organizational structure used does not fit or is incongruent with the mission. Thus, Entin et al. (2003a) predicted and found this pattern of results. To have utility the predicted coordination requests and coordination transfer scores built from the 25% sample regression models must depict a similar pattern. A comparison of the pattern of results derived from coordination requests and coordination transfer scores computed from the whole sample and those scores derived from the 25% sample regression models are shown in Figure 1. As we can see, the patterns for both coordination requests and coordination transfer are quite similar. Moreover, analysis of variance analyses performed with the scores derived from the regression models yielded significant results ($Fs(1, 28) = 20.39$, $ps < .01$, effect sizes = .421), albeit, weaker than those for Entin et al. (2003a), in which the computed effect sizes were $\geq .549$.



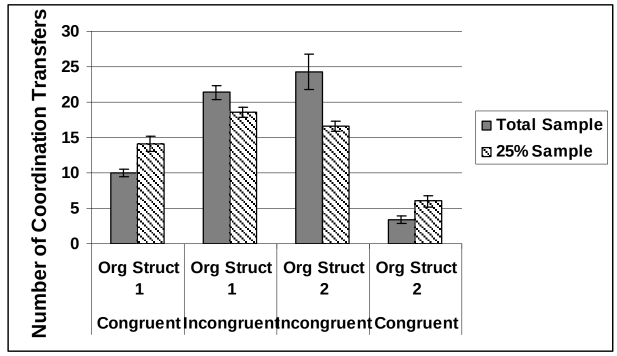


Figure 1 The patterns for the number of coordination requests and transfers by organizational structure and congruence of mission

Discussion & Conclusions

Summary

Our results showed that adequate predictive regression models can be constructed for communication categories using the communication volume for the whole sample. In our example all the corrected part-whole correlations proved significant as were all the regression models. Perhaps, more importantly, adequate regression models can be constructed from a 25% randomly drawn sample. Three out of the four corrected part-whole correlations were significant and the remaining correlation was marginally significant. Similarly, three out of the four regression models were significant. Inspection of the residuals computed from the 25% sample regression models, moreover, did not reveal any serious outliers or influential data points. In short, it appears that the regression models derived from the 25% random sample were similar to the regression models derived from the whole sample. Of equal importance was the finding that the predicted scores from the 25% sample regression models showed similar communication patterns found for scores derived from the whole sample. Analysis of the predicted scores for coordination requests and coordination transfers showed the same mean patterns across the two independent variables as the coordination requests and coordination transfers scores computed from the whole sample. Additionally, analysis of variance analyses revealed that the predicted scores demonstrated a significant interaction similar to that found when scores from the whole sample were used. Not only does the proposed methodology produce adequate regression models, but the models are able to produce scores that, when used in place of scores computed from the whole sample, show the same patterns as scores derived from the whole sample.

We conclude that if an automated application provided measures of communication volume, the proposed methodology could derive reasonable estimates of communication categories without having to code communications for the whole sample. This could afford savings of between 75% and 80% of the usual time and labor required to code communications for a whole sample.

Limitations

Although the methodology described here shows promise to save significant time and effort in coding communications, it is no panacea. Coding of communications for some trials is required.

Someone must expend the effort to become proficient in some form of communication coding and code the required sub-sample. When the overall sample size is small, the methodology probably does not offer sufficient savings given the loss in precision. We estimate that samples of less than 30 trials are not amenable to this methodology. The larger the sample, the larger the potential savings in time and the higher the likelihood a randomly selected sub-sample will adequately represent the whole sample. It should also be obvious that under certain communications environments, like the study described above (i.e., Diedrich et al., 2003), communication volume will be sufficiently related to communication categories to allow construction of predicative regression models. In other cases communication volume will not be sufficiently related and the construction of useful regression model will not be possible. Inspection of the corrected part-whole correlations can help in making a determination to continue. If the researcher deems the part-whole correlations to be too weak to produce adequate regression models than continuation with the methodology would be fruitless.

Conclusion

The findings reported above are encouraging because they open the possibility of reducing the time and effort required to code communications in a study while still deriving useful communication measures. Freed from a substantial portion of the laborious coding task, perhaps more experimenters may be willing to include communication measures that could potentially yield a better understanding of team performance and dynamics in their suite of dependent variables.

References

Diedrich, F.J., Entin, E.E., Hutchins, S.G., Hocevar, S.P., Rubineau, B. & MacMillan, J. (2003). When do organizations need to change (Part I)? Coping with incongruence. *Proceedings of the 2003 Command and Control Research and Technology Symposium*, National Defense University, Washington, DC.

Entin, E. E., Diedrich, F.J., Kleinman, D.L., Kemple, W.G., Hocevar, S.P., Rubineau, B., & MacMillan, J. (2003a). When do organizations need to change (Part II)? Incongruence in action. *Proceedings of the 2003 Command and Control Research and Technology Symposium*, Washington, DC.

Entin, E. E., Diedrich, F. J., and Rubinea, B. (2003b). Adaptive communication patterns in different organizational structures. *Proceedings of the Human Factors and Ergonomics Society 47th Annual Meeting*, Denver, CO.

Entin, E. E. & Entin, E. B. (2001). Measures for evaluation of team processes and performance in experiments and exercises. *Proceedings of the 2001 Command and Control Research and Technology Symposium*. Naval Academy, Annapolis, MD.

Entin, E.E. and Serfaty, D. (1999). Adaptive team coordination. *Human Factors, 41*, 312-325.

Guilford, J.P. (1965). *Fundamental statistics in psychology and education.* New York: McGraw-Hill.

MacMillan, J., Diedrich, F.J., Entin, E.E., & Serfaty, D. (2005). How well did it work? Measuring organizational performance in simulation environments. In W. B. Rouse and K. R. Boff (Eds.) *Organizational Simulation*, John Wiley.

Orasanu, J. M. (1990). *Shared mental models and crew decision making* (CSL Report 46). Princeton, NJ: Princeton University, Cognitive Science Laboratory.