Automatic Modeling of Dominance Effects Using Granger Causality

Kyriaki Kalimeri[1], Bruno Lepri[2,3], Taemie Kim[3], Fabio Pianesi[2], and Alex Sandy Pentland[3]

[1] CIMeC, Corso Bettini 30, 38068, Rovereto Italy
[2] FBK, via Sommarive 18, Povo, Trento, Italy
[3] MIT Media Lab, 20 Ames Street, 02-139 Cambridge, MA

Abstract. We propose the use of Granger Causality to model the effects that dominant people induce on the other participants' behavioral patterns during small group interactions. We test the proposed approach on a dataset of brainstorming and problem solving tasks collected using the sociometric badges' accelerometers. The expectation that more dominant people have generalized higher influence is not borne out; however some more nuanced patterns emerge. In the first place, more dominant people tend to behave differently according to the nature of the task: during brainstorming they engage in complex relations where they simultaneously play the role of influencer and of influencee, whereas during problem solving they tend to be influenced by less dominant people. Moreover, dominant people adopt a complementarity stance, increasing or decreasing their body activity in an opposite manner to their influencers. On the other hand, less dominant people react (almost) as frequently with mimicry as with complementary. Finally, we can also see that the overall level of influence in a group can be associated with the group's performance, in particular for problem solving task.

Keywords: Dominance, Small Group Interactions, Granger Causality

1 Introduction

Management, scientific research, politics and many other activities are accomplished by groups. For this reason, it is increasingly becoming important to understand the dynamics of group interactions and how they relate to group performance. Dominant behavior is a key determinant in the formation of a group's social structure, and consequently, in group dynamics [10]. Many social psychology studies have shown that individuals higher in trait dominance tend to attain more influence in face-to-face interactions [1,10,19]. Moreover, a meta-analysis of 85 years of research found that dominance can predict who emerges as the leader in group interactions more consistently than other individual characteristics, including intelligence [12]. For this reason, in the last years dominance aroused much interest in the automatic behavior analysis community. In particular, different researchers have dealt with the automatic detection of the most dominant person and/or of the least dominant person in small group interactions (e.g. meetings) using different non-verbal acoustic and visual cues [14,7,8,9].

However, to our knowledge there are not works that automatically model the causal effects that people displaying dominant non-verbal behaviors have on the non-verbal behaviors of the other participants. In order to investigate these effects and how they relate to group performance, we apply Granger causality, an approach that detects and estimates the direction of causal influence in time series analysis. To exemplify the approach, in this work we focus on people's body activity and on how it affects the body activity of other group members. In doing so, we investigate the kind of effects dominance display produces on the body activity of the influencees.

Previous studies in social psychology [20] have shown that observers can respond to dominant behaviors with mimicry or complementarity behaviors, where the former amounts to a reproduction of the behavior of the dominant person and the latter to an opposite behavior. Hence, people may respond to dominance displays by exhibiting similar (dominant) behavior and/or respond to submissive behaviors with submissive ones (mimicry). On the other hand, they could also match dominant and submissive behaviors with contrasting behaviors, with dominant displays inviting submissive responses and submissive displays soliciting dominant behaviors (complementarity). According to Chartrand and Bargh[3], mere correlational analysis are not enough to conclude that person X_1 is mimicking (or complementing) person X_2; rather, they can only inform whether X_1 and X_2 are displaying similar or contrasting behavioral patterns at the same time. Those associations, however, could be due to third, confounding, factors that are ultimately responsible for the observed behavioral patterns (e.g. a hot room causing all present to fan their face). In order to conclude for the presence of true mimicry/complementarity, a causal relationship must be proven in which Person X_1 first engages in the particular behavior and then Person X_2 mimics (or complement) that behavior. Granger causality [6] is a promising approach to this end: widely used in neuroscience to infer the existence of causal relationships among neural circuits [18], it has originated in econometrics [6] to detect and model causal relationships among temporal series. To our knowledge, it has been seldom, if ever, applied to the automatic analysis of human behavior [13] and to social behavior, in particular.

2 Twenty-Question Game Dataset

The dataset consists of 13 groups with 4 participants. Each participant wore a sociometric badge - a wearable electronic badge with multiple sensors collecting interaction data. By interacting with other badges, it can collect proximity data, other badges in direct line of sight, body movement data by means of accelerometers, and speech features. In this paper, we use only the accelerometer data and more specifically the variation of body movement energy, obtained by computing the amplitude of the movement vector in the *3*-dimensional space

(x,y,z). An example of the participants wearing sociometric badges can be found in Figure 1.

Fig. 1. Meeting participants wearing the sociometric badges

The data encompass two co-located meeting types, brainstorming and problem solving. The task used is based on a modification of the game "Twenty-Questions", which integrates both brainstorming and problem-solving scenarios by closely replicating Wilson's experiments [21]. At the beginning of a task, each group was given a set of ten yes/no question-and-answer pairs. For the first phase of each task, groups were given 8 minutes to collaboratively brainstorm as many ideas that satisfy the set of question-and-answers. Then, continuing into the second phase, groups were given 10 minutes to ask the remaining ten questions of the Twenty-Question Game to determine the correct solution.

2.1 Dominance

In the post-task questionnaire, one of the questions asked users to rate the self-perceived level of dominance. The subjects answered using a 5-point Likert scale. Following [11], the participants with values higher than one standard deviation over the mean were considered dominant. We also asked all the participants to rate each other's dominance level and as for self-perceived dominance the participants with values higher than one standard deviation over the mean were labelled as dominant.

2.2 Performance

The performance scoring is determined by (i) the number of correct ideas in the brainstorming phase and (ii) the number of questions used to arrive at the correct answer in the problem-solving phase. As the goal of brainstorming is to generate as many ideas as possible. We use the total number of ideas generated as a measure for the performance of the brain- storming phase. In the problem solving phase, groups were asked up to 10 questions to find the correct solution. They received a higher score if they used fewer questions and a zero score if they could not get the answer correct within 10 questions. Hence, we use the number of questions each team used as a negated measure of the team's performance.

3 Our Approach

To understand the direction of the influence flow in social interactions, it is of fundamental importance to distinguish the driver from the recipient. One of the most prominent methods to estimate the direction of the causal influence in time series analysis is the Granger Causality(GC)[6]. This method is based on asymmetric prediction accuracies of one time series on the future of another. In specific, let two time series X_1 and X_2,

$$X_1(t) = \Sigma_{j=1}^{p} A_{11,j} X_1(t-j) + \Sigma_{j=1}^{p} A_{21,j} X_2(t-j) + \xi_1(t)$$

$$X_2(t) = \Sigma_{j=1}^{p} A_{21,j} X_1(t-j) + \Sigma_{j=1}^{p} A_{22,j} X_2(t-j) + \xi_2(t)$$

where A is the matrix containing the coefficients of the model and ξ_1,ξ_2 are the residuals of X_1 and X_2 respectively. A time series X_1, is said to Granger-cause X_2 if the inclusion of past observations of X_1 reduces the prediction error of X_2 in a linear regression model of X_2 and X_1, as compared to a model including only the previous observations of X_2. An important aspect of GC is its generalizability to the multivariate case in which the GC of X_1 on X_2 is tested in the context of multiple additional variables (in our scenario the other two meeting participants W and Z). In this case, X_1 is said to Granger-cause X_2 if knowing X_1 reduces the variance in X_2's prediction error when all the other variables are also included in the model [5]. In our case, the time seriesX_1, X_2, X_3, X_4 of the system $\mathbf{X}$ are reffering to the body movement of each of our subjects as described above. To remove every linear trend from the data, all series have been detrended and their temporal mean has been removed as an initial preprocessing step. We estimate the best order of the multivariate autoregressive model (MVAR) using the Bayesian Information Criterion (BIC)[15]. The estimated model was further checked both (i) to control whether it accounted for a sufficient amount of variance in the data and (ii) using the Durbin-Watson [4] test to validate whether its residuals are serially uncorrelated. Then, once the set of significant lagged values for X_2 is found, the regression is augmented with lagged levels of X_1. Having estimated the G-causality magnitudes, their statistical significance was evaluated via an F-test on the null hypothesis that the coefficients $A_{i,j}$ are zero. If the coefficients in the corresponding $A_{i,j}$ were jointly significantly different from zero, then the causal interaction was considered to be statistically significant. To correct the tests from multiple comparisons, the Bonferroni correction [2] approach was chosen thresholded at $\frac{P}{n(n-1)}$, with P=0.01.

Let our small group of participants be a small causal network of 4 interacting nodes. In causal networks, nodes represent variables and the directed edges represent causal interactions.A measure of the causal interactivity of a system $\boldsymbol{X}$ is the causal desity [16], which is defined as the mean of all pairwise G-causalities between system elements, conditioned on the system's statistically significant interactions.

$$cd(X) \equiv \frac{1}{n(n-1)} \Sigma_{i \neq j} F_{X_i \to X_j | X_{[ij]}}$$

where $X_{[ij]}$ is the network from which the variables X_i and X_j are omitted. For each of our nodes (i.e. each subject), we estimate the unit causal density $cd_u(i)$ which is the summed causal interactions involving a node i normalized by the number of nodes. In particular, we computed two versions (i) one weighted by the GC magnitudes, *weighted unit causal density* (WUCD) and (ii) the unweighted *unit causal density* (UCD) obtained by setting all the significant causal interactions to 1. The nodes with high values of UCD or WUCD can be considered to be the causal hubs inside the meeting. Furthermore, to identify nodes with distinctive causal effects on the network dynamics, we estimated the *causal flow* of a subject X_1, both weighted by the Granger magnitudes (WFLOW) and unweighted (FLOW). The causal flow is defined as the difference between the in-degree and the out-degree of a given node. Therefore, a subject with a high positive causal flow exerts a strong causal influence on the meeting and it can be called causal *source*. On the other side, a subject with a highly negative causal flow can be called a causal *sink*. From the GC relationships in the causal network, we are only able to determine if the body activity of subject X_1 has a causal effect on the body activity of subject X_2; however, we are not able to discriminate between mimicry and complementarity effects.

In order to assess these phenomena, we investigated the correlation between the time series of the subjects for which we found some significant causal effect. For example, once determined that subject X_1 Granger-causes X_2, we checked if the correlation among the time series X_1 and the time series X_2 is positive, revealing mimicry effects, or is negative, showing complementarity ones.

4 Experimental Results

First of all, we focus our attention on the relationships between influence,behavior and the dominance scores. Our expectation is that more dominant people have generalized higher influence, measured in terms of higher UCD and/or WUCD; positive and higher flow; higher out-flow. As a first step we compute the Spearman rank-correlation between a number of GC-related quantities (UCD, WUCD, FLOW, WFLOW, Out and In) and the dominance scores both those obtained on the basis of self-assessment (DomSelf) and those provided by the other members of the group (DomOther). In both cases, ranks are computed on a group-by-group basis. The results are reported in the Table 1. As emerges from them, the rank correlations are uniformly low and non-significant, with the exception of the correlation between the self-dominance rank and the Flow rank and of

Table 1. Rank Correlations between GC quantities and dominance scores

	BrainS	BrainS	ProS	ProS
Rank	DomSelf Rank	DomOtherRank	DomSelf Rank	DomOtherRank
UCD	0.66	0.085	- 0.123	-0.197
WUCD	0.057	0.096	-0.119	-0.96
FLOW	-0.035	-0.077	-0.320	-0.153
WFLOW	0.014	-0.049	-0.256	-0.103
Out	0.100	0.058	-0.188	-0.138
In	0.100	0.155	0.081	0.054

the correlation between the self-dominance rank and the WFLOW rank. In both cases, they are negative, so that more dominant people tend to have lower values of both simple and weighted causal flow in the problem solving condition. None of these results seems to support our expectations. In order to deepen our analysis, we classified our subject along two dimensions, the first (BrainS) addresses their behavior in the brainstorming session and the second (ProS) does the same for the problem solving session. The two dimensions consist each of four classes:

- Class "0": the subject was neither a source nor a target of influence
- Class "1": the subject acted only as a source of influence
- Class "2": the subject acted only as a targets of influence from other subjects
- Class "3": the subjected acted both as a source and a target of influence

The distribution of subjects according to the two classification schema is as in Figure 2.

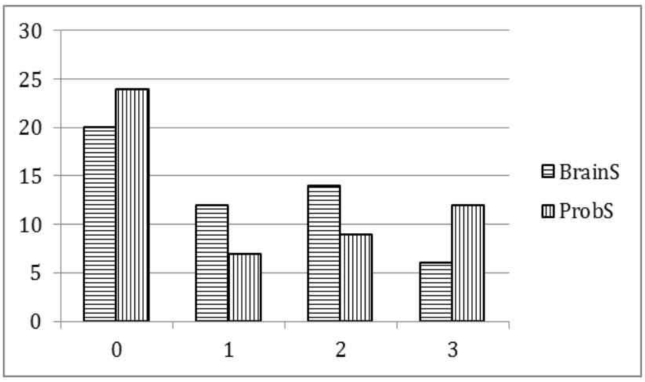

Fig. 2. The distribution of subjects according to the two classification schema

As can be seen, both in the brainstorming and in the problem solving conditions a large part of our subjects never took part in any influence exchange. On the other hand, the number of those who acted both as targets and as sources doubles in the ProS conditions, with a marked decrease of those playing just one of those two roles. Moreover, the number of those influence exchanges involving the same two people as both influencers and influence increases from just 1 pair in the BrainS condition to 4 couples in the ProS one; in other words, of the 12 people falling in class “3” in the ProS condition, 8 are part of influencer/influencees dyads. Summarizing, once the subjects who do not take part in any influence interaction are set apart, it seems that, in problem-solving people are more willing to get involved in complex influence interactions, whereas they stick more to a mono-directional format while brainstorming. We now compute the average and median dominance ranks for each behavior class. The results are reported in the Table 2.

As observed, both in the brainstorming and in the problem solving conditions a large part of our subjects never took part in any influence exchange. On the other hand, the number of those who acted both as targets and as sources doubles in the ProS conditions, with a marked decrease of those playing just one of those two roles. Moreover, the number of those influence exchanges involving the same two people as both influencers and influence increases from just 1 pair in the BrainS condition to 4 couples in the ProS one; in other words, of the 12 people falling in class “3” in the ProS condition, 8 are part of influencer/influencees dyads. In summary, once the subjects who do not take part

Table 2. Average and Median Dominance Ranks for each Behavioral Class

	DomSelf Rank	DomOtherRank	DomSelf Rank	DomOtherRank
BrainS	Average	Median	Average	Median
Class0	2.52	2.5	2.53	2.5
Class1	2.21	2.00	2.08	1.75
Class2	2.36	2.00	2.46	2.75
Class3	**3.33**	**3.50**	**3.33**	**3.5**
ProS	Average	Median	Average	Median
Class0	2.52	2.00	2.58	2.50
Class1	2.07	2.00	2.29	2.50
Class2	**3.00**	**3.00**	**2.83**	**3.00**
Class3	2.33	2.25	2.21	2.00

in any influence interaction are set apart, it seems that, in problem-solving people are more willing to get involved in complex influence interactions, whereas they stick more to a mono-directional format while brainstorming. The average and median dominance ranks for each behavior clas are reported in the Table 2. The average and median ranks for the two dominance assessment (self vs. other) are substantially consistent. Interestingly, a trend emerges for higher dominance rankings to fall in class “3” of the BrainS classification and in class “2” of the ProS one. In other words, the subjects who act both as influencers and influences while brainstorming tend to be higher in dominance, while, in turn, the most dominant subjects seem to play the role of influencees in the problem solving condition. This latter fact explains, at least in part, the significant negative correlations between the two measures of causal flow and the dominance ranking in the ProS condition. The Figure 3 reports the correlation between the performance scores in the BrainS and ProS conditions and two measures of overall (body activity based) group-internal amount of influence. The first, AV-UCD, is the average value of the so-called Unit Causal Densities (UCD), which measures the causal density of a given person in terms of the number of incoming and outcoming influences he/she plays a role in. The second quantity, Av-WUCD, is the average of the Weighted Causal Densities (WUCD), which weights the casual density of a given person in terms of the GC values attached to the single influences he/she participates in.

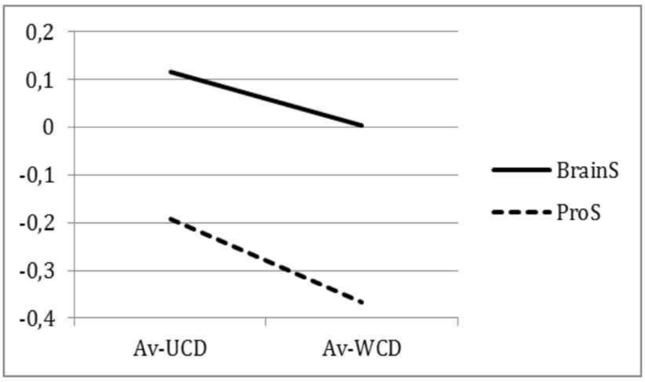

Fig. 3. Correlation between the performance scores in the BrainS and ProS conditions and the group causal densities

Whereas the correlation values are either very close to zero for the BrainS condition, they have higher negative values in ProS. Recalling that the highest performance in the ProS condition correspond to a score of zero (zero question asked to reach the conclusion), it can be concluded that an increase of body-motion related influence during problem solving corresponds to a moderate increase in performance. No interesting trend emerges in the brainstorming condition.

We conclude the analysis of the data concerning the relationships between dominance and influence by considering what happens when influence relations involve subjects of unequal dominance status - that is the relationships where one of the subject scores highest in the group and the other is lower. There are two fundamental modes described in the literature[20] in which influence can unfold: the influencee follows the behavior triggered by the influencer (mimicry) or he/she can exhibit the opposite behavior (complementarity). In our case, we can capture these differences by computing the correlation between the two corresponding signals: if there is an influence relationship (that is, the GC is significant) and the correlation is positive, then we speak in terms of mimicry, otherwise, we consider it as a case of complementarity. Given the exploratory nature of this paper, we have retained all the correlation coefficients corresponding to any significant influence relationship.

The results are promising: out of 10 cases in which a dominant person affects a non-dominant one, 6 were cases with mimicry (positive correlation) and 4 cases of complementarity; when the influence relationship was reversed and a non-dominant person affected a dominant one, only in 3 cases out of 14 there was mimicry.

5 Conclusion

The expectation that more dominant people have generalized higher influence (higher UCD and/or WUCD; positive and higher flow; higher out-flow) is not borne out; rather more nuanced patterns emerge. In the first place, more dominant people tend to behave differently according to the nature of the task: during brainstorming they engage in complex relations where they simultaneously play the role of influencer and of influencee, whereas during problem solving they tend to be influenced by less dominant people. However, while doing so, they adopt a complementarity stance, increasing or decreasing their body activity in an opposite manner to their influencers. On the other hand, when less dominant people are the target of influence from more dominant ones, they react (almost) as frequently with mimicry as with complementary.

We have also seen that there are signs that the overall level of influence in a group can be associated with the group's performance, and that this seems to be the case in problem solving condition; an interesting question could be whether this is related in any way with the fact that dominant people play more often the role of influence targets in this condition, this way possibly making it possible to more focused effort to be deployed.

Before concluding, we emphasize the exploratory nature of this study and the fact that, with a few exceptions (GC values and correlation values in Table 1) none of our suggestions is supported by statistical evidence, because of the limited size of the used sample. Still, we believe that we have shown the power of the notion of Granger causality and the flexibility it allows for in the investigation of complex social phenomena.

6 Acknowledgements

Bruno Lepri's research was funded by the Marie Curie COFUND 7th Framework PERSI project.

References

1. Aries, E.J., Gold, C., Weigel, R.H. Dispositional and situational influences on dominance behavior in small groups. Journal of Personality and Social Psychology. 44, 779-786 (1983).
2. Benjamini, Y., Hochberg, Y. Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing. Journal of the Royal Statistical Society. Series B (Methodological). 57, 289-300 (1995).
3. Chartrand, T.L., Bargh, J.A. The chameleon effect: the perception-behavior link and social interaction. Journal of Personality and Social Psychology. 76, 893-910 (1999).
4. Durbin, J., Watson, G. Testing for serial correlation in least squares regression.I. Biometrika. 37, 409-428 (1950).
5. Geweke, J. Measurement of Linear Dependence and Feedback Between Multiple Time Series. Journal of the American Statistical Association. 77, 304-313 (1982).
6. Granger, C.W.J. Investigating causal relations by econometric models and cross-spectral methods. Econometrica. 37, 424-438 (1969).
7. Hung, H., Jayagopi, D., Yeo, C., Friedland, G., Ba, S., Odobez, J.-M., Ramchandran, K., Mirghafori, N., Gatica-Perez, D. Using audio and video features to classify the most dominant person in a group meeting. Proceedings of the 15th international conference on Multimedia. pp. 835-838. ACM Press (2007).
8. Hung, H., Jayagopi, D.B., Ba, S., Odobez, J.-M., Gatica-Perez, D. Investigating automatic dominance estimation in groups from visual attention and speaking activity. Proceedings of the 10th international conference on Multimodal interfaces IMCI 08. pp. 233-236. ACM (2008).
9. Jayagopi, D.B., Hung, H., Yeo, C., Gatica-Perez, D. Modeling Dominance in Group Conversations Using Nonverbal Activity Cues. IEEE Transactions on Audio, Speech and Language Processing. 17, 501-513 (2009).
10. Judge, T.A., Bono, J.E., Ilies, R., Gerhardt, M.W. Personality and leadership: a qualitative and quantitative review. Journal of Applied Psychology. 87, 765-780 (2002).
11. Kim, T., Chang, A., Holland, L., Pentland, A. Meeting mediator: enhancing group collaborationusing sociometric feedback. CSCW. pp. 457-466 (2008).
12. Lord, R.G., De Vader, C.L., Alliger, G.M. A meta-analysis of the relation between personality traits and leadership perceptions: An application of validity generalization procedures. Journal of Applied Psychology. 71, 402-410 (1986).
13. Prabhakar, K., Oh, S.M., Wang, P., Abowd, G.D., Rehg, J.M. Temporal causality for the analysis of visual events. CVPR. pp. 1967-1974 (2010).
14. Rienks, R., Zhang, D., Gatica-Perez, D., Post, W. Detection and application of influence rankings in small group meetings. ICMI. pp. 257-264 (2006).
15. Schwarz, G. Estimating the Dimension of a Model. The Annals of Statistics. 6, 461-464 (1978).
16. Seth, A.K. A MATLAB toolbox for Granger causal connectivity analysis. Journal of Neuroscience Methods. 186, 262-273 (2010).
17. Seth, A.K. Causal networks in simulated neural systems. Cognitive neurodynamics. 2, 49-64 (2008).
18. Seth, A.K., Edelman, G.M. Distinguishing causal interactions in neural populations. Neural Computation. 19, 910-933 (2007).
19. Smith, J.A., Foti, R.J. A pattern approach to the study of leader emergence. The Leadership Quarterly. 9, 147-160 (1998).

20. Tiedens, L.Z., Fragale, A.R. Power moves: complementarity in dominant and submissive nonverbal behavior. (2003).
21. Wilson, D.S., Timmel, J., Miller, R.R. Cognitive cooperation: when the going gets tough, think as a group. Human Nature. 15, 225-250 (2004).