Conversation, Coupling and Complexity: Matching Scaling Laws Predict Performance in a Joint Decision Task

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Abstract

We investigate the linguistic co-construction of interpersonal synergies. By applying a measure of coupling between complex systems to an experimentally elicited corpus of joint decision dialogues, we show that interlocutors' linguistic behavior displays increasing signature of multi-scale coupling, known as *complexity matching*, over the course of interaction. Furthermore, we show that stronger coupling corresponds with more effective interaction, as measured by collective task performance.

Keywords: Linguistic interaction; Complexity matching; Scaling Laws; Joint Decision Making.

Introduction

Language as Joint Action

Recent approaches to linguistic conversation consider language in terms of joint action (Clark, 1996; Galantucci & Sebanz, 2009). Through dialogue, interlocutors are observed to coordinate behaviors on multiple levels, from subtle bodily sways (Shockley, Richardson, & Dale, 2009) to alignment of syntax and high level situation models (Pickering & Garrod, in press). These findings have often been related to priming mechanisms on the level of individual cognition: by perceiving and interpreting linguistic forms, interlocutors prime each other to produce similar forms and therefore becomes increasingly aligned over time (Pickering & Ferreira, 2008). An increasing number of studies suggest, however, that linguistic coordination is more than just increased similarity between individuals or behaviors. It enables *interpersonal synergies*, where the interlocutors' actions and cognitive processes become nonlinearly *coupled*, i.e. multiplicatively interdependent (Dale, Fusaroli, Duran, & Richardson, in press; Fusaroli, Raczaszek-Leonardi, & Tylén, accepted; Riley, Richardson, Shockley, & Ramenzoni, 2011). An important argument for the linguistic co-construction of interpersonal systems has been to show how linguistic coordination enables augmented or even otherwise impossible cognitive processes (Fusaroli, Gangopadhyay, & Tylén, in review; Hutchins & Johnson, 2009; Theiner, Allen, & Goldstone, 2010). In this paper, we complement the existing focus on the end results of interaction approaching the interaction dynamics itself: What aspects of interaction dynamics provide the basis for co-constructed interpersonal systems? We investigate the general hypothesis that a statistical coupling in scaling law relations of speech signals corresponds with interpersonal synergies created in dialog. This coupling is theorized in terms of complexity matching (West, Geneston, & Grigolini, 2008), and is shown to increase with more effective linguistic interactions, as measured by collective task performance.

Linguistic Complexity Matching

Complex systems – such as human beings – produce sequences of outcomes with long-range correlations at strongly interacting time scales. In other words, the different time scales at which we can analyze human behavior are interacting according to scaling laws and are evidenced by heavy-tail distributions such as lognormal or Pareto distributions (Kello et al., 2010; Riley & Van Orden, 2005). Recent work has proposed that the coupling of two complex systems can be assessed by their *complexity matching*, that is, the matching of the scaling laws exponents (Aquino, Bologna, West, & Grigolini, 2011; West, et al., 2008). While initially developed for the description of physical systems, the notion of complexity matching has recently been successfully applied to very basic interpersonal coordination tasks (Marmelat & Delignières, 2012).

While scaling laws have been shown in several non-interactional linguistic phenomena (Kello, Anderson, Holden, & Van Orden, 2008; Kello, et al., 2010), linguistic behavior during actual conversations has not yet been analyzed from this perspective. However, seminal work indicates how speech production is matched between interlocutors on a number of individual time scales: short term respiration rhythms (McFarland, 2001), turn-taking timing (Wilson & Wilson, 2005), and longer term patterns of interaction (Levitan & Hirschberg, 2011). In this study we investigate the presence of scaling laws and the matching of temporal complexity in conversational acoustic production between interlocutors, thus considering multiple time scales at once. Building on the idea that language enables interpersonal coordinative coupling, we hypothesize that:

1. Linguistic coordination between interlocutors shows scaling laws, that is, interaction-dominant dynamics indicative of self-organization (Van Orden, Holden, & Turvey, 2003).
2. Speech event scaling law exponents match between interlocutors in a dyad.
3. Such complexity matching increases over time, as the dyad develops coordinative routines.
4. Not all dyads will present the same level of complexity matching. The stronger the matching, the better the joint cognitive performance of the dyads.

To test these hypotheses, we rely on a video corpus of task-oriented conversations where dyads had to repeatedly make joint decisions (Bahrami et al., 2010; Fusaroli et al., 2012). The corpus granted us sequences of linguistic interactions and measures of dyads' collective task performance, allowing for the investigation of the development of linguistic complexity matching and its effectiveness. The complexity of each interlocutor's speech events for each trial of the joint decision task was assessed in both the frequency and temporal domain employing methods based on multi-model inference (Burnham & Anderson, 2002) and Allan factor (Allan, 1966).

Materials and Methods

The corpus consisted of approximately 20 hours of video recording of sixteen dyads (n=32, 14 m/18 f, mean age 25.2, SD=6.9, all native speakers of Danish who had given informed, written consent) that each performed on average 92 (SD = 15.5) joint decision trials for a total of 1472 joint decision trials. The participants were recorded while sitting in front of their own respective screen at right angles to each other in a darkened room (see figure 1a). On each trial they were sequentially shown two 85 millisecond long visual displays containing six Gabor patches (see figure 1c). By pressing buttons, the participants had to individually indicate which of the displays contained a contrast oddball. As long as both participants gave the same answer they would automatically proceed to the next individual trial. However, if their individual choices disagreed, they were prompted to negotiate, by freely discussing with each other, a joint decision. There was no time or other constraints on the joint decision dialogues. Mid-way through the experiments there was a break and the participants were asked to exchange seats, thus generating two experimental sessions.

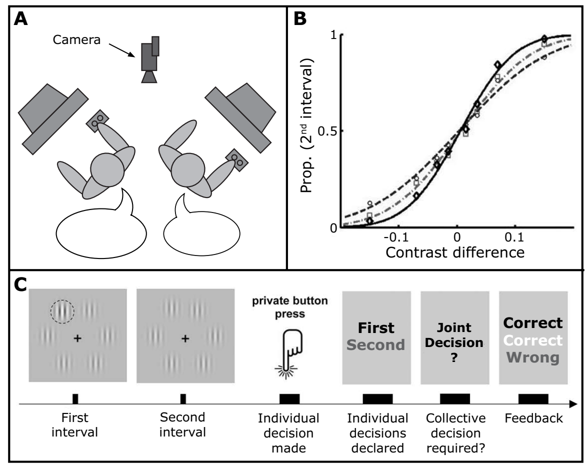

Figure 1: Experimental setup (Adopted with permission from Fusaroli, et al., 2012). (a) The experimental setup. (b) Group average psychometric functions that relates the individual and group choice to stimulus strength. The proportion of trials in which the target was reported to be in the second interval is plotted against contrast difference at the oddball location. Circles: average performance of the less sensitive dyad members; squares: average performance of the more sensitive dyad members; diamonds: average performance of the dyads. (c) Schematic illustration of a typical trial.

Measuring Interpersonal Performance

Psychometric functions were estimated for each dyad member and for the dyad by calculating the proportion of trials in which the oddball was reported in the 2nd interval versus the contrast difference at the oddball location (see figure 1b). Using the slope measure of the psychometric function, we quantified individual dyad members' as well as the dyad's sensitivity and defined "collective benefit" as the ratio of the dyad's slope to that of the more sensitive dyad member. A collective benefit value below 1 would indicate that collaboration was counterproductive (the dyad did worse than its more sensitive member), while a value above 1 would indicate successful cooperation, i.e. that the dyad gained a benefit relative to its more sensitive member (for more details on the psychometric function, cf. Bahrami, et al., 2010).

Measuring Linguistic Complexity

The complexity of the interlocutors' linguistic behavior was analyzed by identifying the distributional shape and temporal structure of the speech event data through two complementary analyses. The former requires a distributional analysis that chooses the best fitting distribution from a set of candidate distributions. The latter requires investigating the temporal correlations of the behavior of interest. Observed behaviors that are correlated over long ranges of temporal scales tend to follow a *1/f* scaling relation (Van Orden, et al., 2003).

The videos from the sixteen dyads were annotated at a 10 ms scale for speech events, pauses and turn-taking dynamics employing a combination of listening, audio-wave inspection and automated analysis of pitch and intensity using Praat (Boersma, 2001) and MATLAB (Mathworks, inc). Pauses were defined as reduced intensity and lack of pitch lasting beyond .2 seconds. From the linguistic behavior of each interlocutor during each joint decision we then extracted the onset/offset intervals of the acoustic signal. These were used to investigate the distributional properties of speech events. To test for long-range correlations of speech events, we computed a binary spike train for every trial of each interlocutor's acoustic signal. The binary spike train entailed a sequence of zeros and ones, where "1" would indicate an onset or an offset of a speech event, that is the change from silence to sound or vice versa. Each binary spike train (by trial per interlocutor) was used as the input for an Allan Factor analysis. This method will be discussed below.

Estimating the Distributional Properties of Speech Events

As a preliminary step, we utilized a maximum likelihood method termed multi-model inference (MMI, Burnham & Anderson, 2002) to identify the best fitting statistical distribution in onset/offset interval distributions. MMI assesses the likelihood for a given set of data to be generated from each of several candidate model distributions. Importantly, the method accounts for differences in free parameters among candidate distributions by computing Akaike's information criterion (AIC) from maximum likelihood values. We included distributions into the candidate set that are known to have heavy tails (e.g., lognormal, Pareto, and gamma) and those known not to have heavy tails (e.g., Gaussian and exponential).

Distributions of onset/offset intervals for every joint decision trial for each interlocutor in the 16 dyads (2739 trials total) were tested against five different functions using multi-model inference: Gaussian, exponential, lognormal, Pareto, and gamma. AIC values showed that the lognormal function was most likely to generate the distributions for most onset/offset interval distributions (82% of all trials), with Pareto distribution being most likely to generate the majority of the remaining trials (18% of all trials). Both lognormal and Pareto distribution are heavy-tailed. Given the large predominance of lognormal distributions, we estimated the parameters (μ and σ) of the lognormal distribution for further analysis. The μ provides information about the mean/mode of the lognormal distribution, whereas the σ provides the variance or skew in the tail of the asymmetric distribution (see figure 2b).

Estimating the Temporal Structure of Speech Events

We estimated scaling laws in the temporal domain of the spike trains of speech events by using the Allan factor analysis (AF, Allan, 1966). Events were counted in adjacent windows of time with increasing scales, and the normalized squared differences between windows of the same scale were averaged. When events are Poisson distributed, average squared differences by window size remain constant over increasing window size, whereas, event structures that are power law-like fall into nested clusters of window size where the normalized squared differences will approximate a power law function of window size (Kello, in press; Lowen & Teich, 2005; Thurner et al., 1997).

Formally, given a sequence of counts N in a time series of length L, where N_j is the number of events in the jth window of size T, we first compute the differences in counts of events between adjacent windows:

$$d(T) = N_{j+1}(T) - N_j(T), \qquad (1)$$

The Allan factor A for a given time window T is the expected value of the squared differences, normalized by mean counts of events per window,

$$A(T) = \frac{\langle d(T)^2 \rangle}{2\langle N(T) \rangle}. \qquad (2)$$

Poisson processes yield $A(T) \sim 1$ for all T, whereas power law clustering yields $A(T) \sim (T/T_1)^{\alpha}$, where T_1 is the smallest time scale considered, and α the exponent of the scaling relation. Normalized, continuous point processes with $\alpha \sim 0$ are Poisson-distributed (i.e., uncorrelated temporal structure). By contrast, continuous point processes with α near the upper bound of $\alpha \sim 1$ are highly-clustered, power law-like temporal structures and can be considered fractal stochastic point processes (Thurner, et al., 1997). See figure 2a and 2c for a graphical depiction of the Allan Factor analysis of speech events.

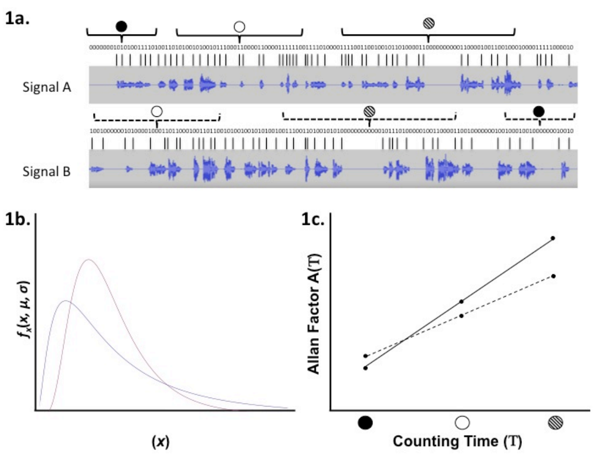

Figure 2: Overview of analyses. (Adopted with permission from Abney et al., submitted). (a) Transformation from wave form to speech event point process and to binary spike train. (b) Idealized lognormal probability density plot. Note differences in σ between two distributions: a heavy tail and a normal one. (c) Idealized plot of Allan Factor estimates for each window size, *T*. Note the differences in slope between Signal A and Signal B from 1a.

The AF analysis of speech events provides a measure of temporal complexity for each trial and each interlocutor in a dyad. Thus, we can track the trial-by-trial unfolding of complexity of individuals and of the coordination between interlocutors in a dyad.

Measuring Complexity Matching

We assessed complexity matching by correlating the trial-by-trial complexity indexes of the interlocutors within each dyad. This process was performed on the overall sequence of trials and on a session-by-session basis – to observe the temporal evolution of complexity matching. For the distributional analysis we employed the σ (the variance of its normal, unlogged, counterpart, a measure of the heaviness of the tail of the distribution) as complexity index, while for the temporal analysis we employed *A* (the Allan Factor).

In order to control for incidental complexity matching due to task structure and not actual linguistic interaction, we created virtual dyads: i.e., for each dyad we matched the individual interlocutors' complexity indexes with all the interlocutors with whom she had not engaged in dialogue and averaged the complexity matching values achieved.

To control for effects due to simple local dependencies akin to behavioral synchrony (e.g. Interlocutor A starts speaking as a reaction to interlocutor B ceasing to speak), we computed the mutual information, a non-linear analogous to cross-correlation (MI, Kraskov, Stögbauer, & Grassberger, 2004), for the two signals in real and virtual dyads. We tested for mutual information at lags comprised between – 20 seconds and + 20 seconds. Since we found the highest mutual information at lag 0, we only report statistics for that lag value.

Finally, we employed the Pearson coefficient of the complexity matching as an index of the strength of the matching and correlated it with collective benefit. All analyses were performed in Matlab (Mathworks, inc).

Results

Performance

In terms of task performance, dyads gained a significant collective benefit in the perceptual decision-making task, compared to the better member of each dyad: $M = 1.18$, $SD = 0.25$, $t(15) = 2.84$, $p = .01$. However, not all dyads did equally well and 3 out of 16 dyads did not gain a collective benefit (i.e. did not exceed their respective best member's individual performance). This variation in collective benefit suggests that not all dyads achieved the same degree of functional, interpersonal coupling.

Complexity Matching

Distributional Shape: Analysis of the σ of the lognormal distribution showed that 8 out of 16 dyads display a significant negative complexity matching ($r_{mean} = -.18$, $SD = .07$). The absolute coefficient of matching is significantly higher than in virtual dyads ($r_{mean} \sim 0$, $SD = .04$): $t(15) = 5.88$, $d = .70$, $p < .001$. Complexity matching in this domain did not show any significant difference between sessions.

Interlocutors displayed significantly higher mutual information in the frequency domain than virtual pairs, $t(15) = 3.74$, $d = .43$ $p = .006$. However, mutual information was low ($M = .01$, $SD = .004$), displayed a decrease over time ($t[15] = 7.70$, $d = 0.80$, $p < .001$) and did not correlate with complexity matching, nor with collective benefit. Thus no evidence was found for local, within-trial coordination between interlocutors.

Temporal structure: For the complexity of temporal structure analyzed by the AF, 11 out of 16 dyads displayed a significant positive complexity matching ($r_{mean} = .25$). Complexity matching was significantly higher than in virtual dyads ($r_{mean} \sim 0$), $t(15)= 24.31$, $d = 0.97$, $p < .001$, and significantly increased over sessions: $t(15) = -3.38$, d = .52, $p = .004$.

In the temporal domain, interlocutors displayed significantly higher mutual information than virtual pairs ($t[15]= 3.86$, $d = 0.50$ $p=.0015$). However, mutual information was low ($M=.00001$, $SD=.00001$), displayed a significant decrease over time, ($t[15]=3.04$, $d = 0.38$, $p=0.008$) and did not significantly correlate with complexity matching, nor with collective benefit.

Complexity Matching and Performance

Coefficients of complexity matching from the distributional analysis did not correlate with collective benefit.

However, in the temporal domain the coefficients of complexity matching displayed a very significant correlation with collective benefit: $r = .61$, $p = .012$ (see fig. 3a). Interestingly, while the strength of complexity matching in the first session did not significantly correlate with collective benefit (it did display a trend: r = 0.47, p = .069, see fig. 3b), a strong correlation was found in the second session: r = .72, p = .0025 (see fig. 3b). A stepwise forward regression with collective benefit as dependent variable was run to assess the relative role of complexity matching in the two sessions. The resulting model only contained complexity matching from session 2 and excluded complexity matching from session 1 (r=-.011, p=.961), suggesting that achieved complexity matching subsumes and overrides initial complexity matching. Finally, the change in complexity matching – measured as the slope between sessions – was also found to correlate with collective benefit: r=0.47, p= 0.048.

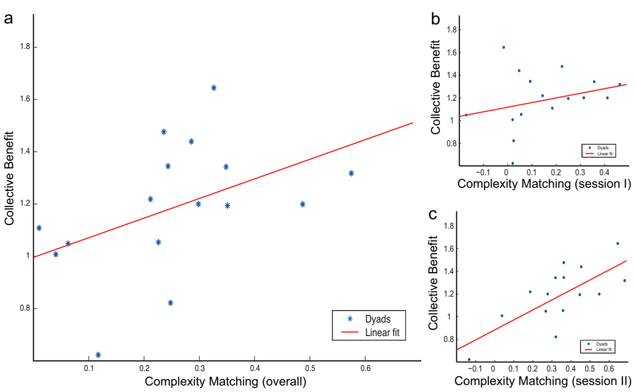

Figure 3: Correlation plots. (a) Correlation between collective benefit and overall complexity matching in the temporal domain. (b) Correlation between collective benefit and complexity matching in the first session. (c) Correlation between collective benefit and complexity matching in the second session.

Discussion

In the previous sections, we have approached linguistic interaction from the perspective of interpersonal coupled systems: To co-construct such systems, dyads must finely coordinate action on multiple levels and time scales. Moreover, the joint task performance of a conversing dyad should depend on the degree of functional coupling between the interlocutors, to the extent that an interpersonal system is co-contructed in the service of task performance. Our findings seem to support such predictions.

The overall results of the distributional properties and the temporal structure of interlocutor speech events suggest lognormal fits in the former and variable amounts of correlated clustering of speech events in the latter. The temporal structure of speech events displays significant between-interlocutor complexity matching, not found in virtual dyads. Interestingly, the degree of complexity matching was significantly predictive of dyads' collective performance benefit. This effect is consistent with the finding that complexity matching increased over time. This suggests that functional interpersonal coupling is not immediately achieved but evolve through repeated interaction presumably as an effect of coordinative routines and interdependencies being developed.

These effects cannot be attributed to distributional properties of the speech events evidenced by the lack of matching between the σ of two interlocutors in a dyad. Furthermore, the effects of complexity matching cannot be attributed to a local coordination, as measured by mutual information—that is, complexity matching was not a product of speakers simply matching their utterances, or regularly alternating their turns. Lastly, the results cannot be attributed to the structure of the task, since they are not observed in virtual dyad controls, nor to simple initial matching, since complexity matching in the first session does not correlate with collective benefit.

This is not to say that task structure does not have an effect. Abney et al. (submitted) recently observed the degree of complexity matching in dyadic interaction to be modulated as a function of the external constraints imposed on the dyadic system (in this case affiliative vs. argumentative conversational topics). Our current findings are commensurate with Abney et al. and complement them by introducing a more explicit investigation of the temporal development of complexity matching.

The development of interpersonal synergies over time

We observe that complexity matching in the temporal domain is statistically more significant and informative than complexity matching in the frequency domain. The importance of temporal dynamics is also emphasized by the temporal development of complexity matching and mutual information. Mutual information decreases across sessions while complexity matching increases, suggesting that initial local coordination (akin to behavioral synchrony) might be employed initially only to be replaced by more complex forms of coordination at later stages (Dale, et al., in press; Fusaroli, et al., accepted). The correlation of complexity matching with collective benefit also increases across sessions.

In conclusion, linguistic interactions enable augmented or innovative end results in ways that display signatures of strong coupling with corresponding functional effects. In the context of physical systems these signatures have been shown to be indicative of self-organization on a superordinate level. The establishment of interaction-dominated dynamics in task-oriented conversation strengthens the idea of conversations as interpersonal synergies. Moreover, the observed graded complexity matching and its relation to collective benefits suggests that interpersonal synergies are not static qualities but rather a question of degree, time and skill.

The methods here developed show much promise for the study of a wider variety of linguistic interactions and aspects of interpersonal coordination.

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