Pink noise in speakers' semantic synchrony dynamics as a metric of conversation quality

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Abstract

Dyadic social interaction is a complex coordination task involving a large number of interconnected variables. Previous research has shown that metastability – persistence for an extended, but impermanent, period of time in a non-stable state of a system – can be a useful lens for understanding what makes an interaction successful. However, this framework has thus far only been applied to para-conversational signals like heart rate and prosody – not to the semantic content of a conversation. Here, we present pink noise analysis of semantic trajectories as a metric for conversational success and apply this technique to a large open conversation dataset. Our results demonstrate that pink noise in a conversation predicts a host of variables representing participants' perception of conversation quality. These results have implications for optimizing a whole host of difficult dyadic conversations – like those between political partisans – and human-computer interactions, with applications for improving large language models' adaptability.

Keywords: Dynamical systems; Interactive behavior; Natural language processing; Situated cognition; Social cognition

Introduction

When we enter into a conversation with another person, we're immediately faced with a complex coordination task. We must make inferences about the other's beliefs and goals, curate what information we present about ourselves, intuit when it is appropriate to start or stop talking, and manage countless other negotiations that allow for fluid conversation. With so many interacting features at play, modeling dyadic conversation can quickly become intractable. Studying dyadic interaction in terms of interpersonal synchrony can be a helpful way to manage that inherent complexity. Synchrony can be operationalized in a variety of ways (see (Butler, 2011) for a review) and applied to a variety of domains, but generally serves as a measure of time-linked similarity between two signals. Previous studies have measured synchrony during dyadic interactions in neural activity (Kinreich, Djalovski, Kraus, Louzoun, & Feldman, 2017; Levy, Lankinen, Hakonen, & Feldman, 2021), body movements (Paxton & Dale, 2013; Hale, Ward, Buccheri, Oliver, & Hamilton, 2020), prosody (Pérez, Gálvez, & Gravano, 2016), heart rate (Coutinho et al., 2021), and more.

Much of the interpersonal synchrony literature focuses on synchrony as a predictor of success in a social interaction (see (Mogan, Fischer, & Bulbulia, 2017) for a review). However, some recent papers have suggested that synchronizing with an interactive partner can be maladaptive in certain scenarios: over-synchronization can lead to poorer ability to self-regulate one's emotions and worse outcomes on complex joint problem-solving tasks (Abney, Paxton, Dale, & Kello, 2015; Timmons, Margolin, & Saxbe, 2015; Feniger-Schaal, Hart, Lotan, Koren-Karie, & Noy, 2018; Pérez et al., 2016; Galbusera, Finn, Tschacher, & Kyselo, 2019). In response to these seemingly contradictory findings, a subliterature has emerged that highlights the importance not of (a)synchrony itself, but of social partners' ability to adaptively move in and out of synchrony (Mayo & Gordon, 2020; Wallot, Mitkidis, McGraw, & Roepstorff, 2016; Dahan, Noy, Hart, Mayo, & Alon, 2016; Hale et al., 2020; Wohltjen & Wheatley, 2021; Ravreby, Shilat, & Yeshurun, 2022).

Borrowing from the language of complex dynamical systems (see (Kelso, 2021)), this idea of adaptive movement in and out of synchrony with a social partner can be operationalized as pink noise, or $\frac{1}{f}$ noise scaling. In pink noise, the log-frequency and log-power of a signal (here, synchronization between social partners) are inversely related, meaning that there is more power (i.e., higher-amplitude fluctuations) in the lower frequencies. Pink noise signals appear in healthy coordination tasks all across human physiology, from EEG activity (Kerr et al., 2012) to walking pace (Raffalt, Sommerfeld, Stergiou, & Likens, 2023). Thus far, pink noise in dyadic interaction has been studied in the context of para-conversational synchrony – signals like heart rate or finger tapping. Here, we demonstrate that this approach can be extended to the actual semantic content of a conversation.

Methods

Dataset

We tested for the presence of metastable semantic synchrony in an open dataset, CANDOR (Reece et al., 2023), consisting of 1,656 conversations in English between participants recruited through Prolific. Participants were instructed to talk as if they had just met at a social event, for at least 25 minutes (mean length: 31 minutes; SD: 7.96 minutes). Before and after each conversation, participants took extensive surveys about their personalities and experiences. We separated the 205 survey questions that resulted in numerical responses into 6 categories: those relating to (1) conversation enjoyment, (2) sense of ongoing connection, (3) engagement with and mem-

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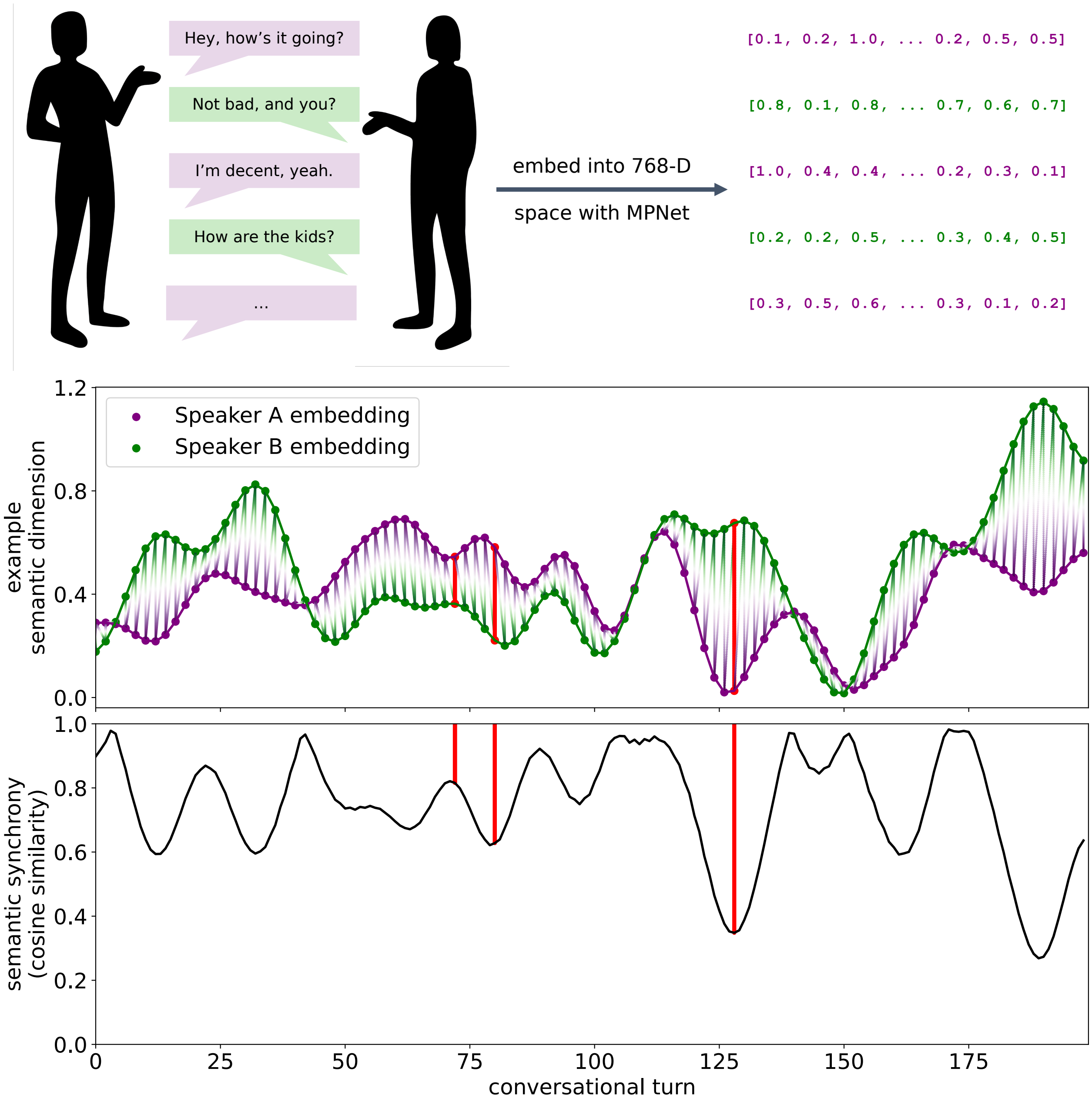

Figure 1: Calculating semantic synchrony timecourse for an example conversation. Each turn of the conversation is embedded into high-dimensional encoding space with a transformer model. Then, the cosine similarity between each pair of adjacent turns is used to calculate a continuous measure of semantic synchrony.

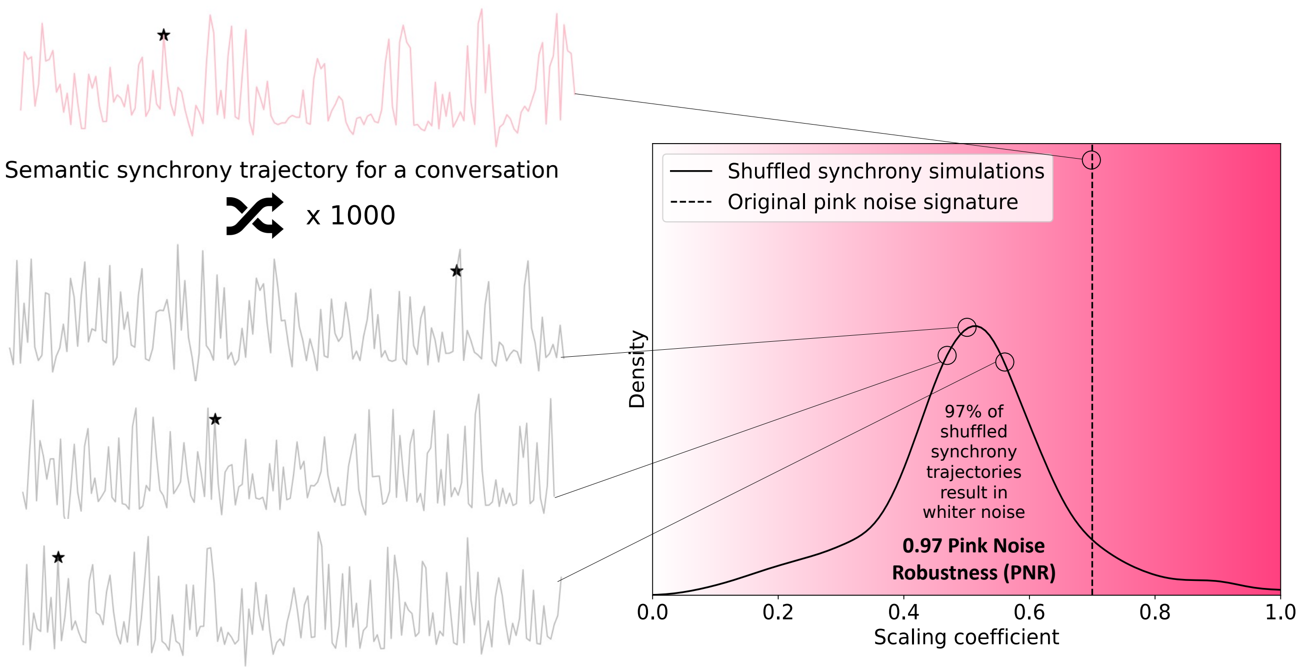

Figure 2: Calculating a pink noise robustness score for an example conversation. Each conversation's semantic synchrony signal is time-scrambled 1,000 times in order to generate a distribution of scaling coefficients which do not depend on interlocutors' mutual adaptation over time.

ory for the conversation, (4) demographics and low-level conversation statistics (like average turn length and number of laughs), (5) how each participant rated their partner on various trait batteries, and (6) how each participant scored on those trait scales themselves.

Pink noise analysis

Our method for evaluating the strength of pink noise signals in these conversations consisted of 4 steps: embedding the transcript into high-dimensional large language model space, generating a semantic synchrony signal, calculating the scaling coefficient for this signal, then comparing this coefficient against a simulated distribution to calculate a metric we term Pink Noise Robustness.

First, we segmented each conversation transcript into a list of conversational turns, splitting the text each time a new speaker begins an utterance (Figure 1, top left). Then, we used the Python package *sentence-transformers* (Reimers & Gurevych, 2019a) to embed each turn into high-dimensional semantic space (Figure 1, top right), turning each speaker's half of the conversation into a trajectory through this space (Figure 1, middle). The results in this paper were generated using *all-mpnet-base-v2* and its 768-dimensional space, but we also calculated scaling coefficients for each of the 1,656 conversations in the CANDOR corpus using roBERTa, sBERT, and LaBSE to ensure that this method is robust to different embedding regimes (Liu et al., 2019; Reimers & Gurevych, 2019b; Feng, Yang, Cer, Arivazhagan, & Wang, 2022).

To calculate the semantic synchrony signal, we took the cosine similarity of the embedding of each conversational turn and the following embedding (Figure 1, middle and bottom). For a conversation consisting of N turns, this gave us a length $N-1$ measure of how closely aligned conversational partners were in their semantic content at each timepoint. While there are many potential ways to generate this semantic synchrony signal (e.g., splitting into sentences, using a fixed-length window), we were most interested in how dyads co-navigate synchrony through turn-taking, so we treated a conversational turn as our fundamental unit.

To assess the color of noise present in each conversation's semantic synchrony signal, we used detrended fluctuation analysis (DFA; (Rydin Gorjão, Hassan, Kurths, & Witthaut, 2022)) to obtain a noise scaling coefficient. This scaling coefficient essentially represents the log-log relationship between a signal's frequency and power, indicating the signal's self-affinity. A scaling coefficient of 1 indicates pink noise, while lower values indicate whiter noise and higher values indicate redder noise.

Because semantic embeddings are a higher-dimensional signal than previously assessed measures like eye contact or heart rate (Wohltjen & Wheatley, 2021; Wallot et al., 2016), there was a considerable amount of room for the undue influence of factors unrelated to adaptive conversation techniques. For example, if an artificial transcript was compiled by putting together the utterances of Speaker A from one conversation and Speaker B from another conversation, the resultant semantic synchrony signal would often contain pink-to-red noise signatures. This is not, however, because these two unrelated speakers are actually adapting to each other. This result would be an artifact of extended sections of low-synchrony signal, which presents as low-frequency fluctuation. To test the robustness of any pink noise signatures we found in a conversation's semantic synchrony, we compared the signal's scaling coefficient to a distribution of null scaling coefficients generated by scrambling the semantic synchrony signal 1,000 times. This gave us a Pink Noise Robustness (PNR) value: the proportion of scaling coefficients from the scrambled distribution that were lower (i.e., whiter noise) than that of the original signal (Figure 2).

Predicting conversation variables

Each conversant in the CANDOR conversation corpus filled out an extensive survey after their conversation, resulting in 3,312 total survey responses. We filtered for questions with numeric answers that were answered by over 500 participants (mean = 2598 responses; std = 1096 responses). This left 205 survey variables, which we separated into 6 categories: those relating to conversation enjoyment (25 questions), sense of ongoing connection (16 questions), engagement with and memory for the conversation (20 questions), demographics and low-level conversation statistics (48 questions), how each participant rated their partner on various trait batteries (41 questions), and how each participant scored on trait scales themselves (55 questions).

We then tested how strongly a conversation's Pink Noise Robustness (PNR) was associated with participants' responses to each survey question. For continuous variables, we calculated Pearson correlation, and for discrete survey variables, we calculated Spearman correlation between the survey variable and PNR. We used two different forms of multiple hypothesis correction to generate two sets of conversation variables strongly associated with PNR. For a more stringent significance cutoff (i.e. fewer variables, but smaller risk of Type 1 errors) we used Bonferonni correction, and for a more lenient significance cutoff (i.e. more PNR-linked variables, but slightly higher risk of Type 1 errors) we used Benjamini/Hochberg False Discovery Rate (FDR) correction. Additionally, we performed principal component analyses within each question category, and predicted the score on the first principal component for each conversation with a linear model of the form $category\_composite \sim conversation\_PNR + speaker\_PNR + mean\_synchrony$.

We then tested two alternative hypotheses: (1) that positive conversation variables can be predicted by average synchrony alone, rather than the mutually-adpative synchrony signal characterized by pink noise, and (2) that positive conversation variables do not depend on dyadic adaptation, but rather the pink noise signatures present in the individual trajectories of each interlocutor.

Results

Semantic synchrony trajectories in dyadic conversations exhibit pink noise signatures

Detrended fluctuation analysis (DFA) of the CANDOR conversation semantic synchronies yielded a distribution of scaling coefficients ranging between white and pink noise, with a shift towards pinker noise (min = 0.34, max = 0.98, mean = 0.62; Figure 3, top left). First, we wanted to ensure that this result was robust to choice of sentence embedding model. Coefficients derived using MPNet were highly correlated to those derived using three other models: roBERTA ($R2 = 0.83, p < 0.001$), sBERT ($R2 = 0.63, p < 0.001$), and LaBSE ($R2 = 0.55, p < 0.001$) (Liu et al., 2019; Reimers & Gurevych, 2019b; Feng et al., 2022)). Second, we wanted to capture the degree to which any pink noise present in a conversation's semantic synchrony trajectory could be attributed to participants' dynamic adaptation – as opposed to other latent features in the turn embeddings. To isolate this effect, we took each conversation's semantic synchrony trajectory and shuffled its order 1,000 times, recalculating the scaling coefficient each time (Figure 3, top left). Then, we compared the original scaling coefficient to this distribution of values, using the proportion of shuffled-synchrony scaling coefficients that resulted in a lower scaling coefficient (i.e., whiter noise) as a metric of Pink Noise Robustness (PNR). This resulted in a left-tailed distribution of PNR values (mean = 0.82, median = 0.91), indicating that a grand majority proportion of conversations in the CANDOR corpus contained pink noise signatures largely attributable to participants' turn-by-turn dynamic navigation in and out of semantic synchrony (Figure 3, bottom left).

Pink noise robustness selectively predicts post-conversation evaluations of enjoyment and connection

We then tested whether conversations' Pink Noise Robustness (PNR) scores could predict the results of the interlocutors' post-conversation surveys. When we correlated PNRs with the 205 survey variables across conversations, 49 of those variables were significantly predicted by PNR under Benjamini/Hochberg FDR correction, and 12 of those were significantly predicted by PNR under stricter Bonferonni correction (Figure 3, right):

1. Total conversation time
2. How enjoyable did you find the conversation?
3. Was there any point during the conversation at which you think your partner felt ready for the conversation to end?
4. How much did your conversation partner self-disclose to you?
5. The things you and your partner discussed felt very real
6. To what extent did your partner find you friendly?
7. To what extent did your partner find you competent?

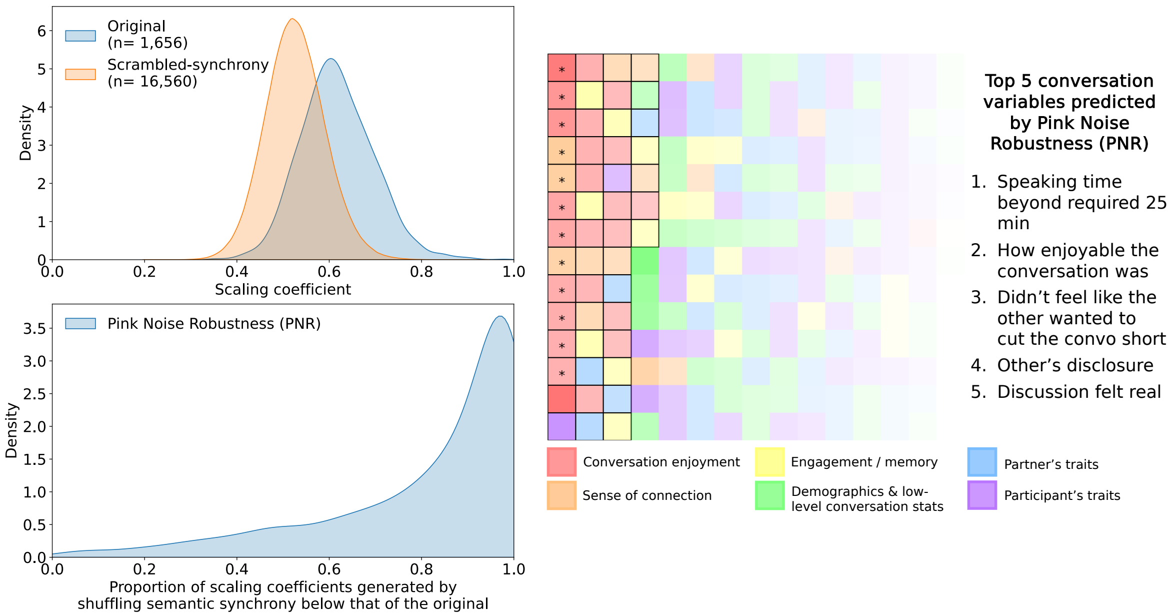

Figure 3: Presence, robustness, and implications of pink noise signatures in CANDOR conversations. Top left: Distributions of scaling coefficients derived from original and scrambled synchrony trajectories. Bottom left: Distribution of pink noise robustness values. Right: Depiction of 205 conversation variables. Color represents category membership, and transparency represents strength of correlation with PNR. Boxes outlined in black represent variables which were found to be significantly correlated with PNR after FDR correction. Asterisks represent variables which were found to be significantly correlated with PNR after Bonferonni correction.

8. How much did you self-disclose to your conversation partner?
9. How much do think your conversation partner liked you?
10. Imagine the next 7 days of your life. If you had the option, how many of those days would you like to have another conversation with the person you just talked to?
11. To what extent did your partner find you warm?
12. How much longer do you think your partner would have liked to continue the conversation?

To test whether the connection between PNR and conversation enjoyment was stronger than that between PNR and other kinds of conversation variables, we sorted the 205 survey questions into categories we defined post-hoc: those relating to conversation enjoyment, sense of ongoing connection, engagement with and memory for the conversation, demographics and low-level conversation statistics, how each participant rated their partner on various trait inventories, and how each participant scored on those trait scales themselves. In both the Bonferonni-corrected and Benjamini/Hochberg FDR-corrected sets of variables, variables in the enjoyment and connection categories were significantly overrepresented ($X^2 = 42,\ p < 0.001$ and $X^2 = 54,\ p < 0.001$ respectively; Table 1).

	All variables	Bonferonni	FDR
Enjoyment	12%	75%	49%
Connection	8%	25%	19%
Engagement	10%	0%	16%
Other traits	20%	0%	10%
Self traits	27%	0%	4%
Low-level	23%	0%	2%

Table 1: Category-wise percentages of all variables and those still significantly correlated with PNR after Bonferonni and Benjamini/Hochberg FDR correction

For the linear models of form $category\_composite \sim conversation\_PNR + speaker\_PNR + mean\_synchrony$, conversation PNRs were significantly predictive of conversation enjoyment and connection ($p < 0.003$ and $p < 0.03$ respectively), while individual speakers' PNRs did not significantly predict any of the category composites. This suggests that true mutual adaptation – rather than individuals' decontextualized movement through semantic space – is what drives enjoyment and connection. Average conversational synchrony, on the other hand, was a significant *negative* predictor of all six category composites. This indicates that overall synchrony was not conducive to enjoyment and connection in this dataset, did not operate specifically on enjoyment, and could not explain away the variance in enjoyment and connection accounted for by PNR.

Discussion

In this study, we have demonstrated that (a) pink noise signatures exist in semantic – not just physiological – synchrony between dyads engaged in conversation, (b) these signatures are driven by interlocutors' dynamic adaptations to each other, and (c) that the strength of these signatures are specifically predictive of interlocutors' perceptions of enjoyment and closeness in conversation. Using just the transcript of a conversation, we can measure how effectively two people navigate the complex dynamics of moving in and out of semantic synchrony with each other: deciding when to ask a follow-up question, move the conversation in a new direction, or add relevant information.

This method has broad applications for analyzing and improving the quality of dyadic conversations in many domains. In conversations where people from different backgrounds or ideologies must come together to build shared understanding, pink noise can serve as a helpful guide for navigating the presentation of differences and commonalities. In educational contexts, the back-and-forth between teachers and students as they tackle complicated learning goals can be viewed through the lens of adaptive (a)synchrony. Large language models that keep track of their ongoing semantic synchrony trajectory with users could use this signal to adapt more flexibly and naturalistically to users' needs.

More broadly, this approach embraces the dynamic complexity inherent to natural conversation. By using mathematical tools that were built for understanding systems as a whole – rather than focusing on individual pieces – we can better understand conversation as an embodied and embedded cognitive process.

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