

A Similarity Measure for Comparing Conversational Dynamics

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Abstract

The quality of a conversation goes beyond the individual quality of each reply, and instead emerges from how these combine into interactional dynamics that give the conversation its distinctive overall “shape”. However, there is no robust automated method for comparing conversations in terms of their overall dynamics. Such methods could enhance the analysis of conversational data and help evaluate conversational agents more holistically.

In this work, we introduce a similarity measure for comparing conversations with respect to their dynamics. We design a validation procedure for testing the robustness of the metric in capturing differences in conversation dynamics and for assessing its sensitivity to the topic of the conversations. Finally, to illustrate the measure’s utility, we use it to analyze conversational dynamics in a large online community, bringing new insights into the role of situational power in conversations.

1 Introduction

In a conversation, individual utterances combine to form interactional patterns, such as exchange structures (e.g., brief exchanges vs. extended back-and-forth), changes in tone (e.g., from passive-aggressive to defusing), and conversational strategies (e.g., concessions or challenges). Each of these patterns contributes to shaping the conversation’s overall *dynamics*, and none of them alone is sufficient to characterize it (Hua et al., 2024).

These emerging conversational dynamics are closely tied to the perceived quality of the conversation and its outcome (Stasi et al., 2023; D’Costa et al., 2024; Liao et al., 2023, inter alia). As such, a measure comparing conversations with respect to their overall dynamics can enhance our ability to analyze human-human and human-AI conversational data. For example, it can be used to group

conversations according to their dynamics and distinguish those that are likely to lead to positive outcomes. This type of analysis could enable a more holistic evaluation of conversational agents, one that goes beyond optimizing for the quality of each response to encourage overall dynamics that are desirable.

However, developing a method for comparing conversations with respect to their overall dynamics presents several challenges. The first challenge is finding an appropriate way of representing the dynamics of a conversation: it is not sufficient to detect individual patterns separately, as done by prior work (e.g., speech acts, empathy, politeness, sarcasm) (Ghosh et al., 2017; Oraby et al., 2017; Chhaya et al., 2018; Danescu-Niculescu-Mizil et al., 2013). Instead, a representation of the overall dynamics must capture how relevant patterns of different types connect to each other. For example, a passive-aggressive tone changing into a defusing tone leads to a very different dynamic than when a defusing tone is followed by a passive-aggressive tone.

The second challenge arises when comparing dynamics. Dynamics take place at multiple scales, with some patterns spanning single exchanges (e.g., a sarcastic response) and others spanning the entire conversation (an increasingly escalating tone). Furthermore, a single utterance can contribute to multiple patterns (e.g., an utterance can be a sarcastic response and simultaneously be part of an increasingly escalating tone). This inherent overlap makes it hard to align the dynamics of two conversations in order to quantify how similar they are.

In this work, we address these challenges to introduce a similarity measure for conversational dynamics: ConDynS (read as “condense”). We address the first challenge by representing dynamics as a sequence of relevant interactional patterns in a conversation (a sequence of patterns, henceforth the *SoP*), extracted from a summary of conversa-

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tional dynamics (Hua et al., 2024). This representation captures not only which interaction patterns are present in a conversation, but also the order in which they follow each other.

We address the second challenge by designing an asymmetric procedure for aligning conversational dynamics (Figure 1). The main intuition behind this procedure is to combine the advantage of the SoP representation—which allows checking the order in which interaction patterns appear—with the advantage of a simple transcript representation—in which we can find patterns with high-recall, even when they are overlapping.

To validate the effectiveness of ConDynS and compare it with baseline measures using other representations or alignment methods, we introduce a human-in-the-loop procedure for generating labeled data. ConDynS recovers these labels with over 90% accuracy, substantially outperforming the baselines, while being robust against changes in topic.

Finally, we demonstrate how a similarity measure for conversational dynamics can enable new types of analysis by applying ConDynS to conversations from a large online debate community. First, it allows us to adapt standard similarity-based techniques—clustering, inter-group similarity, and intra-group diversity—to study conversational dynamics. Second, we use our measure to investigate which participants are more likely to influence the dynamics of a conversation, providing new insights into the role of situational power in conversations.

In summary, in this work we introduce a similarity measure for comparing conversational dynamics. We introduce a validation procedure that allows it to compare it with other baseline measures. And we showcase its use in analyzing online discussions. To encourage further applications, we also make our code publicly available as part of ConvoKit, including demos in other domains.¹

2 Further Related Work

Evaluating conversation-level similarity. Prior work on measuring conversation-level, rather than utterance-level, similarity is limited. Lavi et al. (2021) adapts edit distance to measure similarity of “dialogue flow”, by defining substitution cost based on the semantic similarity of utterances. Other methods (Bhaumik et al., 2023) additionally consider semantic features specific to task-oriented

interactions, such as agent intent. In contrast, ConDynS is not concerned with the topic or semantics of what is discussed, focusing solely on interactional patterns and the emerging dynamics.

Other measures focus on a few predefined features, such as dialog acts (Enayet and Sukthankar, 2022), sentiment (Xu et al., 2019), and number of words per turn (Appel et al., 2018). Our measure instead captures how multiple types of interactional patterns combine, without predefining what types of dynamics to consider.

Representing conversations as sequences. Even though not explicitly defining a similarity measure, several studies represent conversations as sequences of predefined dialog units and aggregate them to compare groups of conversations. Mirza-khmedova et al. (2023) introduces sequences of argumentation strategies previously defined by Morio et al. (2019). Wang and Cardie (2014) represents a conversation as the flow of sentiment in its utterances. Unlike the SoP representation we use, these sequence representations focus on a single predefined dimension of the conversation.

Synthetic conversations. LLMs have been used to generate and annotate datasets across NLP tasks (see Tan et al. (2024) for a survey) including in the conversational domain (Wang et al., 2024; Louie et al., 2024; Liu et al., 2024), sometimes with expert human input (Louie et al., 2024). We build on this work to design our validation procedure, which uses human-written summaries to generate conversations with labels for relative similarity.

3 Measure

Measuring the similarity between the dynamics of two conversations involves (1) representing these dynamics and (2) comparing them. Below, we discuss several options for these steps, which combine to form ConDynS and several baseline measures. Here we describe the general approach, and defer to Section 4 for the operationalization in the specific domain of online debate discussions.

3.1 Representing conversational dynamics

Conversational dynamics are complex, emerging from the progression and juxtapositions of multiple interaction patterns. Therefore, their representation must go beyond describing individual patterns separately (e.g., how polite each reply is, whether it is sarcastic or not, etc.), and instead capture how relevant patterns combine to form the conversation’s

¹<https://convokit.cornell.edu>

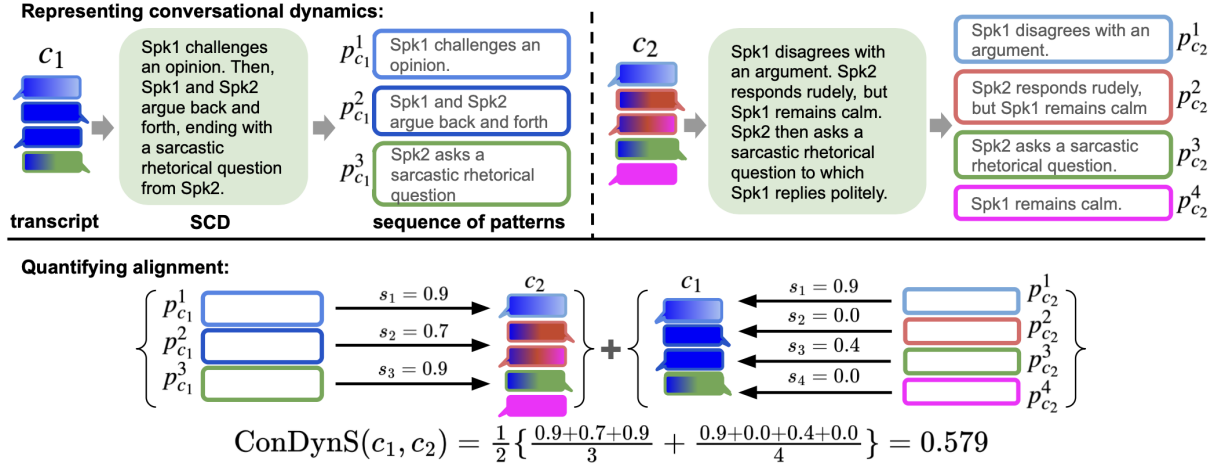


Figure 1: Representing dynamics and quantifying their alignment to calculate ConDynS. Colors represent interactional patterns, sometimes spanning multiple utterances; also, an utterance can contribute to multiple patterns.

dynamics. Given that patterns emerge at multiple scales and are often overlapping, there is an inherent tradeoff between precisely representing a coherent progression and capturing all patterns.

At one extreme, the **raw transcript** offers the most comprehensive representation of a text-based conversation. By preserving all information, it implicitly includes all the patterns that combine to form its conversational dynamics. However, this is a noisy representation as the patterns are not explicitly identified, nor are they separated from the topical context in which they appear. This noise is problematic for our purposes as it might interfere with comparisons focused solely on conversational dynamics. Furthermore, it lacks an explicit ordering of the patterns, making it hard to compare the progression of the interaction.

The **summary of a conversation’s dynamics** (or **SCD**) offers an alternative representation that abstracts away the topical content and explicitly identifies interactional patterns (Hua et al., 2024). Through their abstraction, SCDs select a subset of the interactional patterns that are deemed most relevant to the overall conversation’s trajectory. SCDs thus offer a more condensed and precise representation than the transcripts. This, however, necessarily comes at the expense of recall.

To explicitly capture the order in which individual interactional patterns occur, an SCD can be structured into a **sequence of patterns** (SoP). These are ordered lists of natural language strings extracted from SCDs, each representing one pattern. Figure 1 (top) illustrates the steps of obtaining a SoP from the raw transcript of a conversation, and full examples from our dataset are included in Ap-

pendix B. The exact operationalization of each step is dependent on the application domain, and is detailed in Section 4.

3.2 Comparing dynamics

A straightforward approach to compare dynamics is to measure how well the interaction patterns in one conversation *match* with the ones in the other conversation. Our approach additionally recognizes the role of the order in which patterns appear and quantifies how well the patterns in the two conversations are *aligned*.

Matching: baselines. To form our baselines, we apply existing text-similarity metrics to quantify how well dynamics match across two conversations:

- Cosine similarity of SBERT embeddings: Using a SBERT sentence transformer (Reimers and Gurevych, 2019), we calculate the cosine similarity of the two conversations.
- BERTScore: We use BERTScore (Zhang et al., 2020b) to compare the similarity of the two conversations.
- Naive prompting: We prompt a language model to give a similarity score between 0 and 100 in terms of their dynamics. The prompt is included in Figure 11 and 12.

All these metrics can be applied to either the transcript representation or the SCD representation, resulting in six baseline measures.

Alignment: ConDynS. While straightforward, these matching metrics ignore the order in which the interaction patterns follow each other to give

rise to the overall dynamics. We address that by designing a new metric that quantifies how well the *sequence* of patterns in one conversation aligns with the dynamics of another conversation.

Formally, let $P_{c_1} = [p_{c_1}^1, p_{c_1}^2, \dots, p_{c_1}^n]$ denote the SoP of conversation c_1 . Let c_2 be another conversation with whose dynamics we want to compare; we purposefully defer the discussion of the representation of c_2 . We define an alignment vector

$$s(P_{c_1}, c_2) = [s_1, s_2, \dots, s_n] \in [0, 1]^n, \quad (1)$$

where $s_i \in [0, 1]$ indicates how much $p_{c_1}^i \in P_{c_1}$ contributes to the alignment with the dynamics of c_2 . In addition to rewarding ones that also appear in c_2 , the score is designed to penalize patterns that: (1) appear out of order in c_2 , and (2) are separated in c_2 from the previous pattern in the c_1 sequence (e.g., by other patterns that only appear in c_2). At the extremes, a pattern $p_{c_1}^i$ that does not appear in c_2 will receive a score $s_i = 0$ and a pattern $p_{c_1}^i$ that also appears in c_2 immediately after a pattern matching $p_{c_1}^{i-1}$ will have a score $s_i = 1$.

We average these scores to quantify how well c_1 's sequence of patterns aligns with those in c_2 :

$$(c_1 \rightarrow c_2) \triangleq \frac{1}{|P_{c_1}|} \sum_{s_i \in s(P_{c_1}, c_2)} s_i. \quad (2)$$

We note that this is an asymmetric measure, and that we can analogously compute $(c_2 \rightarrow c_1)$, i.e., how well c_2 's sequence of patterns aligns with those in c_1 .² We average these two asymmetric scores to obtain our similarity measure:

$$\text{ConDynS}(c_1, c_2) \triangleq \frac{1}{2} \{ (c_1 \rightarrow c_2) + (c_2 \rightarrow c_1) \}. \quad (3)$$

In terms of representation, in Eq. (2) c_1 is represented as a SoP to account for the order in which the patterns appear. However, given its asymmetry, we have a choice of how to represent c_2 when calculating the alignment vector $s(P_{c_1}, c_2)$. One option is to also use the SoP representation to focus on the most relevant patterns and exploit their explicit ordering. However, since our goal at this step is to check for the presence of a specific pattern in c_2 , recall is especially important. As such, we propose

²As an extreme example that renders this asymmetry evident, consider a hypothetical case in which c_1 is a conversation starting with all the utterances of c_2 and continuing with more replies. While c_2 's sequence of patterns will align perfectly with c_1 , the sequence in c_1 will not align perfectly due to patterns appearing only in the continuation.

using the most comprehensive representation of c_2 : its raw transcript. This way, the asymmetric nature of the alignment procedure allows us to combine the precision and ordering of the SoP representation with the recall of the transcript representation.

4 Data and Operationalization

Online debate discussions. To validate and demonstrate applications of ConDynS, we use a dataset of conversations from the ChangeMyView subreddit (CMV), retrieved from ConvoKit (Chang et al., 2020). The objective of this platform is for participants (Challengers) to persuade the original poster (OP) to change their viewpoint on an opinion they hold.³ The dataset includes all conversations in the subreddit from its inception, in 2015, up to 2018, and is thus not polluted by content generated by large language models.

This setting has several properties that make it particularly suitable for developing a similarity metric for conversational dynamics. First, it has been a resource for many studies analyzing how conversational features connect to different outcomes—such as successful persuasion (Tan et al., 2016; Priniski and Horne, 2018; Monti et al., 2022; Wei et al., 2016) or conversation derailment (Altarawneh et al., 2023; Kementchedjheva and Sogaard, 2021; Chang and Danescu-Niculescu-Mizil, 2019)—documenting its richness in conversational dynamics. Second, a key feature of the dataset is the “delta” (Δ) mechanism through which the OP can award a Δ to a Challenger that successfully changed their view. This mechanism provides explicit persuasion labels for each conversation, which we will use to interpret our results. Finally, Hua et al. (2024) developed the SCDs procedure on this dataset. As such, they distribute human-written SCDs and provide a validated procedural prompt for automatically generating SCDs, which allows grounding our method and validation procedure in an established framework.

Operationalization. To apply ConDynS and baselines in the context of CMV, we make several implementation choices. The code we release is modular, making it easy to swap specific components to facilitate adaptation to other settings. We use Google’s Gemini 2.0 Flash model (Anil et al., 2024) via their API for ConDynS, including generating

³We follow prior work and consider a conversation to be one linear reply-chain starting with the first comment to the original post introducing the to-be-changed opinion (Chang and Danescu-Niculescu-Mizil, 2019; Hua et al., 2024).

In what percentage of triplets,
 $\text{sim}(\text{anchor}, \text{positive}) > \text{sim}(\text{anchor}, \text{negative})$

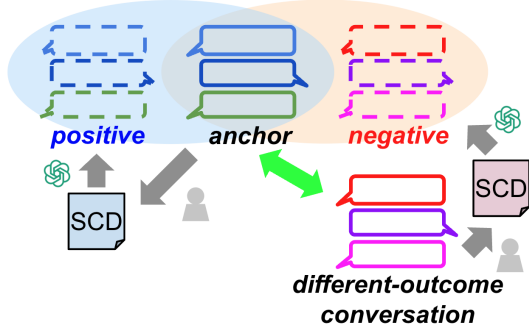


Figure 2: Overview of the validation procedure. Simulated conversations are shown with dashed lines.

SCDs, extracting SoP, and quantifying the alignment of dynamics.⁴ To generate SCDs, we use the procedural prompt validated by (Hua et al., 2024). To measure the alignment scores s_i , we use a few-shot in-context learning prompt with human-constructed examples (showing scoring and reasoning) to quantify alignment. Prompts are included in Appendix A.

5 Validation

No data with labels for similarity of conversational dynamics is available, and the vast space of possible dynamics and their complexity makes human-annotation highly subjective and prohibitively time-consuming (Xu et al., 2019; Lavi et al., 2021). Therefore, to validate our measure and compare it with baseline measures, we design a human-in-the-loop procedure for obtaining synthetic data in which the relative similarity of conversational dynamics is known (Figure 2).

Specifically, we construct triplets of conversations with (1) an *anchor* conversation that serves as the reference for comparison, (2) a *positive* conversation with a dynamic that is known to be similar to that of the anchor, and (3) a *negative* conversation with a dynamic that is known to be different from that of the anchor.⁵ Given a collection of such triplets, we calculate the accuracy of a similarity measure as the proportion of triplets where the anchor-positive pair receives a higher similarity score than the anchor-negative pair.

⁴We also experimented with OpenAI’s latest chatgpt-4o model (Achiam et al., 2024) on the validation set. The results for each measure compare similarly, and are included in Appendix D. We opt for Gemini because it is more cost-effective.

⁵The anchor/positive/negative terminology is not related to sentiment, and is borrowed from (Schroff et al., 2015).

Anchor-positive pairs. Recent work has demonstrated that LLMs can be used to reliably simulate conversations with specific properties (Wang et al., 2024; Liu et al., 2024). We use a similar idea and prompt an LLM to simulate a conversation that closely follows the dynamics of a given anchor conversation. A manual check of the resulting pairs, however, reveals that directly providing the anchor’s transcript in the prompt often leads the model to directly replicate its surface-level features, such as topic, word choice, or speaker turn order, rather than creating an entirely new conversation.

To rectify this, we rely on the SCD abstraction to remove such surface-level features while maintaining the desired dynamics. We prompt the LLM to generate a conversation following the dynamics summarized in the anchor’s SCD. We use human-written (rather than machine-generated) SCDs since they are guaranteed to accurately represent the dynamics as perceived by humans (Hua et al., 2024), while also avoiding circularity with the measures using machine-generated SCDs. This procedure results in a conversation that, while completely new, follows similar dynamics to the anchor conversation, forming the anchor-positive pair.

Generating an anchor-negative pair. To obtain the anchor-negative pair, we must find conversations that are known to differ in their dynamics from the anchor. Drastic differences in outcome can be a good indication that the underlying dynamics are also different (Zhang et al., 2018; Stasi et al., 2023; D’Costa et al., 2024; Liao et al., 2023, inter alia). For each anchor conversation, we pick a different-outcome conversation that is on the same topic and has similar length. Using a human-written SCD of the different-outcome conversation, we simulate a conversation that has similar dynamics to it, and thus different dynamics to the anchor. We use this simulated conversation to form our anchor-negative pair.⁶

To generate the anchor-positive-negative triplets, we make use of the human-written SCDs provided by Hua et al. (2024) for a subset of 50 ChangeMyView conversations. These are paired on outcome, such that each conversation that derails into a personal attack is matched with a similar-topic,

⁶While in principle we could have directly used the different-outcome conversation to form the anchor-negative pair, this would have introduced an asymmetry with how the anchor-positive pair is obtained. One pair would have two real conversations, while the other would have one real and one simulated conversation. Furthermore, the simulation step becomes important for the sensitivity analysis described below.

Measure Representation	ConDynS		cosine sim.		BERTScore		Naive prompting	
	SoP+Trx	SoP	Trx	SCD	Trx	SCD	Trx	SCD
same topic	92%	86%	52%	66%	62%	72%	58%	80%
different topic	94%	80%	50%	74%	56%	72%	68%	72%
adversarial	86%	84%	2%	66%	10%	70%	44%	56%

Table 1: Accuracy of each similarity metric in our validation experiment, for different topic conditions. Each baseline is either given the raw transcript (abbreviated as *Trx* above) as the input or the raw machine-generated *SCD*. The highest score for each topic condition is bolded.

similar-length conversation that does not.⁷ This data allows us to create 50 triplets with known relative similarity.

Sensitivity to topical context. Ideally, a reliable similarity metric for conversational dynamics would not be confounded by topic. To check which measure best embodies this ideal, we impose the topic of the simulated conversations in the triplet to obtain the following conditions: (1) both the positive and negative conversations are assigned the *same topic* as the anchor; (2) both positive and negative conversations are assigned a *different topic* from the anchor; and (3) an *adversarial* condition in which the positive counterpart has a different topic from the anchor, while the negative counterpart is assigned the same topic. The details of the operationalization, including the prompts for identifying and assigning topics are in [Appendix C](#). **Validation results.** [Table 1](#) shows how accurately each similarity measure distinguished between similar (anchor-positive) and dissimilar (anchor-negative) pairs of conversations. ConDynS outperforms all baselines based on matching, in all topic conditions, highlighting the importance of accounting for the order of the interaction patterns through our alignment procedure. Furthermore, aligning the SoP to the transcript, and thus allowing for better recall of interaction patterns, results in additional gains over SoP-to-SoP alignment.

Comparing the representations used in each of the matching-based baselines, we see that the SCD representation leads to better accuracy for all measures. The gains are especially striking in the adversarial topic condition, showing that the abstraction offered by the SCD helps the measures focus on the dynamics and not be distracted by similarities in the topic of the conversation.

⁷According to ([Hua et al., 2024](#)), the SCDs were written by annotators based on truncated transcripts, such that they could not know the actual outcome of the conversations while writing the summaries.

6 Applications

Having verified its effectiveness, we now demonstrate possible applications of ConDynS in analyzing conversational datasets. We start with showcasing three types of standard data analysis techniques for which a similarity metric is needed—clustering, comparing inter-group similarity, and comparing intra-group diversity—and show that ConDynS leads to intuitive results in our online discussions setting (outlined in [Figure 3](#)). We then use our measure to answer new questions about a speaker’s tendency to engage in similar dynamics across different conversations and about how a speaker’s role in a conversation mediates their influence over its dynamics ([Figure 4](#)).

To ensure that results are not driven by basic structural differences like participant count or conversation length, we restrict all our analyses to dyadic conversations of 4-6 utterances,⁸ which include only the OP and one Challenger (with the Challenger always starting the conversation). We leave it to future work to explore dynamics in group conversations.

6.1 Similarity-based data analysis

Clustering. To explore common dynamics in CMV, we cluster a random sample of 200 conversations from the last year of the data (2018) using hierarchical clustering with ConDynS. This involves computing the similarity between all possible pairs of conversations, for a total of 19900 comparisons.

We qualitatively characterize the two top-level clusters by exploiting the natural language representation used by ConDynS. Specifically, we aggregate all patterns that receive an alignment score $s_i > 0.5$ when measuring the similarity of two

⁸We select these conversations that are roughly 5 utterances long because they are long enough to allow dynamics to develop, while also being quite common. We obtain similar results without this strict length control (enforcing only that conversations have at least 4 utterances).

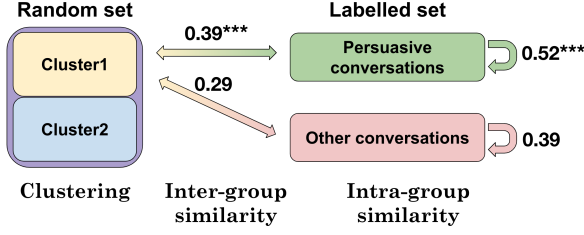


Figure 3: Outline for applying ConDynS to different analyses supported by similarity measures. Statistical significant differences marked with *** ($p < 0.001$).

conversations in the same cluster. We compare the aggregated patterns from the two clusters using a Bayesian distinguishing-word analysis (Monroe et al., 2008), and manually investigate the most distinguishing patterns. The results are summarized in Table 2 and examples of corresponding patterns are provided in Table 5.

The *tone* of the conversation is one of the main components humans consider when describing the conversation’s dynamics (Hua et al., 2024). The tone in Cluster 1 is overwhelmingly positive. Speakers use negative politeness strategies, such as showing gratitude or confirming the other’s points. They are *collaborative*, building upon each other’s argument, and *conciliatory*, apologizing for their misunderstanding or ignorance. In Cluster 2, on the other hand, the tone is generally characterized by dismissiveness and frustration. They are *confrontational*—accusing the other speaker of instigating or being passive-aggressive. In response, the speakers get *defensive* and *sarcastic*—resisting or avoiding direct debates.

Cluster 2’s wide range of *conversational strategies* also suggests an argumentative or potentially contentious interaction. The majority of the speakers express *disagreement* with the other’s argument. The speakers ask a lot of *rhetorical questions* in their responses. They use *straw man fallacies* and *philosophical arguments* and have to *clarify* their reasoning often via *examples* and *analogies*. Conversations in Cluster 1, on the other hand, use detailed *elaboration* to help others understand their arguments. They are more likely to *agree* and acknowledge the validity of the other speaker’s points and concerns; if not, they will *compromise* and concede to points where they share perspectives.

Dynamics are not only characterized by tone or strategies found in single utterances but also by *changes and evolving patterns* through multiple utterances. Cluster 1’s shift in tone is usually to-

	Cluster 1	Cluster 2
Tone	negative politeness collaborative conciliatory	dismissive sarcastic / defensive confrontational
Strategy	elaboration agreement compromise	straw man fallacy disagreement example / analogy seek clarification philosophical direct responses
Changes	changes in view lighter tone	maintains view more contentious

Table 2: Summary of qualitative analysis of the two identified clusters. Examples of corresponding patterns are included in Table 5.

ward a lighter tone (e.g., serious tone to a humorous one). Speakers are also more likely to change or revise their claim through discussion. Cluster 2, on the other hand, becomes more contentious and accusatory, increasing in tension. Speakers’ reluctance to agree often causes initial disagreements to *persist* throughout the conversation, as individuals typically maintain their positions, thereby sustaining the tension.

Overall, this qualitative analysis suggests that the top-level clusters obtained using ConDynS correspond to successful and unsuccessful persuasion attempts. This is expected in an online community focused on debates, further providing face validity to our method. We can also quantify this distinction by using the labels for successful persuasion (Δ). While Δ ’s are rather rare (6.5% of conversations in our random sample receive Δ), Cluster 1 and Cluster 2 show a significant difference in the proportion of conversations that received a Δ (34% vs. 1%, $p < 0.00001$ according to z-test for proportions).

Inter-group similarity. We can further support this interpretation by comparing these automatically detected clusters with a set of conversations that are known to be persuasive. We sample a set of 100 conversations where the OP awarded a Δ (henceforth *set Δ*), and a corresponding set of 100 corresponding conversations which were not awarded a Δ (henceforth *set $\neg\Delta$*).⁹ We find that, as suggested by our qualitative analysis, conversations in Cluster 1 are more similar to those that are known to be persuasive (set Δ) than to those that are not (set $\neg\Delta$): mean ConDynS of 0.39 vs.

⁹We follow (Tan et al., 2016) and select conversations triggered by the same post to control for topic and OP. There is no overlap between these conversations and those in our random sample.

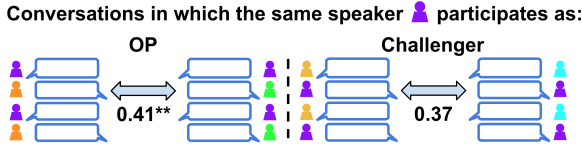


Figure 4: Similarity between two conversations in which a speaker has the role of OP vs. between two conversations in which the *same* speaker is the Challenger. The difference is statistically significant ($p < 0.01$).

0.29, $p < 0.001$ per a Mann Whitney U-test. It is worth noting that this difference remains significant ($p < 0.001$) even if we discard all conversations from Cluster 1 that received a Δ , showing that our method can identify conversations that have persuasive-like dynamics even though their persuasiveness is not explicitly acknowledged by the OP.¹⁰

Intra-group diversity. Finally, we demonstrate the use of our measure to analyze the diversity of dynamics in a set of conversations by calculating intra-group similarity of set Δ and set $\neg\Delta$, respectively. Persuasive conversations are significantly more similar to each other than those in which the persuasive attempt fails (mean ConDynS 0.52 vs. 0.39, $p < 0.001$ according to Mann Whitney U-test; distribution shown in Figure 16).

6.2 New investigation: speakers’ tendencies

The dynamics of a conversation are the results of a joint process involving all speakers. However, similar to how speakers have a tendency to use a specific style *across* different conversations (Welch et al., 2019; Zhang et al., 2020a), they may also have a tendency to engage in certain types of dynamics. In fact, we find evidence to that effect: conversations that share a common speaker have more similar dynamics than those which do not (ConDynS 0.37 vs. 0.35, $p < 0.001$ according to Mann Whitney U-test, comparing random samples of 2000 pairs of conversations).

Provided this observation, a natural question arises: in a conversation involving two speakers, whose tendency is more likely to prevail? In particular, we use our similarity measure to investigate how a speaker’s role in a conversation mediates their influence over its dynamics. Considering the OP and Challenger roles in the CMV setting (Section 4), two hypotheses emerge. The first is based on situational power (Prabhakaran et al., 2014): the

OP ultimately decides whether to award a Δ to the Challenger. Prior work showed that speakers with higher situational power often influence the other speaker’s stylistic (Danescu-Niculescu-Mizil et al., 2012), syntactic (Boghrati et al., 2018), and topical choices (Prabhakaran et al., 2014). Does this influence extend to conversational dynamics?

Alternatively, prior studies emphasize the critical role of persuasion strategies in debates and their outcomes (Braca and Dondio, 2023; Orazi et al., 2025). The Challenger, by selecting the strategy, may dictate the dynamics.

To distinguish between these two hypotheses, we design a setup that controls for speaker-related confounds, such as demographics that might otherwise spuriously correlate with both their role in the conversation and their influence (Figure 4). We select speakers who participate in at least four conversations, each started by a different post: two in which they take the role of OP and two in which they are the Challenger.¹¹

We find that the pair in which the speaker is the OP is more similar than the pair in which they are the Challenger (0.41 vs. 0.37, $p < 0.01$ according to Wilcoxon signed-rank test). This suggests that conversation dynamics are more likely to follow the tendencies of the (higher-powered) OP than those of the Challenger, supporting the first hypothesis.¹² This result complements the above-mentioned studies by providing insights into how a speaker’s situational role in a conversation mediates their influence on its dynamics.

7 Conclusion

In this work we introduce a similarity measure for conversational dynamics and develop a validation procedure to compare different representations and alignment methods. We showcase the measure’s applications in the context of an online debate community, adding to the literature on the relation between situational power and influence in conversations.

Our measure joins a growing toolkit of computational methods for conversational analysis. To encourage its application to other application domains, we make our code publicly available.

¹¹There are 486 such speakers, considering only dyadic conversations that pass our length filters.

¹²We note that this result is not a mere consequence of the number of utterances (in both conditions, the Challenger speaks slightly more than the OP), or of the success of the conversation (no statistical difference in Δ ’s).

¹⁰In contrast, Cluster 2’s similarity to the two labeled sets is not significantly different.

Finally, our measure could be used towards a more holistic evaluation of LLMs’ conversational ability, going beyond the quality of each individual reply to compare systems with respect to the dynamics they engender. Similarity measures like ConDynS can also be a step towards providing conversational-level feedback to AI agents to encourage dynamics that are similar to those preferred by humans (e.g., by extending RLHF).

8 Limitations

ConDynS should not be regarded as a conclusive measure for conversation dynamic similarity, but as a starting point for better approaches. It relies on simple prompting for multiple components, and each of them includes non-trivial tasks. Specifically, we noticed the difficulty of quantifying the alignment of two conversational dynamics. Without a specific rubric, it is difficult to interpret the score outputted by a model. While our measure provides a short description of the analysis for interpretability, there is much room for future work to systematize the scoring standard and procedure.

Moreover, ConDynS requires multiple rounds of generation, which can be very computationally expensive. The entire transcript of each conversation is used as an input twice to calculate the similarity. Optimizing the measure would enable it to scale more effectively to larger datasets.

Our proposed validation carries the shortcoming of relying on synthetic data. Simulated conversations noticeably contained less vulgar and explicit language than real conversations. Such a difference can lead to a discrepancy in performance when the measure is used with real-life data. The reliability of the validation process can be improved by enhancing the quality of the simulated conversations.

More broadly, our analysis is limited to a single domain, which was particularly convenient for developing and validating the measure. Various components (such as the prompts) might need to be adapted in order to apply the method to vastly different domains. By releasing our code in a modular fashion, we encourage adaptations and applications to other domains.

In particular, we only applied ConDynS to online text-based conversations. Future work could study conversation similarity in multi-modal contexts, exploring how to capture dynamics carried out through audio (e.g., voice inflection, tone) or visual (e.g., expressions, gestures) cues and aligning

those dynamics.

Finally, our results provide new insights into the role of situational power in conversations. While in our analysis we control for speaker-specific factors, such as demographics, future work could explore what characteristics beyond the role of the speaker in conversation mediate their influence on the dynamics. Furthermore, combining our measure with a controlled experiment could complement our observational study to elucidate the causal link between situational power and conversational dynamics.

Ethical concerns associated with LLMs in terms of fairness and bias also extend to ConDynS due to its significant dependence on them. Especially during score assignment, the black-box nature of language models is a challenge without a clear rubric that we can rely on to retrace the logic of the models. Therefore, ConDynS may inadvertently reflect or amplify biases the model was exposed to during training.

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A Prompts for ConDynS

In this section, we provide the prompts used in ConDynS. We arrived on these prompts after exploring multiple different versions of the prompt and qualitatively examining the results.

SCD generation. We used the procedural prompt presented in [Hua et al. \(2024\)](#). The prompt is presented in [Figure 5](#).

SoP generation. We prompt a LLM to parse a SCD into a sequence of patterns (SoP). The prompt is presented in Figure 6.

Score assignment. The prompt first introduces the general description of the task and describes the format of the input. The inputs are 1) a dictionary—where the key represents the sequence order of patterns and the value is a description of the pattern identified in SCD—and 2) a transcript of a conversation to compare the dictionary to. Then, it details the specific instructions the model should follow when assigning similarity score for each pattern. Mainly, three main instructions are given:

1. The order in which the patterns occur should be highly considered. In other words, we want to reward when the order of the patterns are maintained in the transcript.
2. Consider whether the transcript closely follow the described sequence. We want to penalize if there are many unrelated patterns or long gaps between the patterns.
3. The pattern can occur between any speakers, and the specific identities of the speakers do not impact the analysis.

The model is asked to provide a score and a short description of the analysis for each pattern in Python dictionary format. The prompt can be found at Figure 7.

B Examples of SCD and SoP

Table 3 shows three examples of SCD and SoP representation. They are machine-generated SCD and SoP of real conversations from CMV dataset. The first two conversations are very similar; the last is very different from the first in terms of dynamics. The entire transcript of each conversation can be found in Figure 8, Figure 9, and Figure 10.

C Validation Details

C.1 Baseline Implementation Details

Cosine similarity. We use a pre-trained sentence BERT model ‘all-MiniLM-L6-v2’ (22.7M parameter in size) to map either the entire transcript or the generated SCD of the conversation into a 384 dimensional dense vector space. Text that is longer than 256 tokens are truncated. The similarity between two conversations is measured by calculating the cosine similarity of their embeddings.

BERTScore. We use a distilled version of the BERT base model (67M parameters) (Sanh et al., 2020) and Huggingface’s BERTScore pipeline to calculate the similarity score.

Naive prompting. We use ‘chatgpt-4o-latest’ model via OpenAI API. The prompt includes the definition of conversation trajectory, specific instructions to consider, output format. The prompt for comparing transcripts can be found at Figure 11. The prompt for comparing SCDs can be found at Figure 12.

C.2 Simulating conversation

For simulating conversations, we use a snapshot of OpenAI’s GPT-4o-mini model from July 18th, 2024 (Achiam et al., 2024), accessed via the OpenAI API due to its cost-efficiency. We ask a language model to recreate an online conversation, given the topic of the conversation and a summary of it’s dynamics. The prompt used for conversation simulation is included in Figure 14.

Alternative approach to simulating. Initially, we simulated conversations with similar dynamics by inputting a conversation transcript. The prompt is included in Figure 13. The simulated conversations, however, were trivially similar to each other in how they carried out the dynamics. They would often copy the exact same sentence structure, sometimes repeat the same words or phrases used in the original transcript, or speaker order—even when it was instructed to generate a conversation with a different topic. Here are some examples:

Example 1:

- Original transcript: “Even if that’s true in the election, it changes the overall vote split between the parties.”
- Simulation: “Even if that’s true, the market is shifting.”

Example 2:

- Original transcript: “isnt that what the king of England wanted from the colonies when we rebelled?”
- Simulation: “Isn’t that kind of like buying a car that’s cheaper upfront but costs more in gas and repairs?”

Such observations highlighted the need for a simulation method that provides the model with the dynamics it needs to follow while not exposing it from the original transcript.

SCD	SoP
1 Speaker2 begins by questioning Speaker1’s stance, expressing doubt and using rhetorical questions. Speaker1 clarifies their position, offering an alternative explanation. Speaker2 identifies a perceived inconsistency in Speaker1’s statements, suggesting a potential dismissal of authentic experiences and appealing to the importance of further study. Speaker1 reiterates their initial claim with conviction, contrasting two different approaches to evidence and emphasizing a lack of progress in one area.	<ol style="list-style-type: none"> 1. Speaker2 questions Speaker1 stance, expressing doubt and using rhetorical questions 2. Speaker1 clarifies their position, offering an alternative explanation 3. Speaker2 identifies a perceived inconsistency in Speaker1 statements, suggesting a potential dismissal of authentic experiences and appealing to the importance of further study 4. Speaker1 reiterates their initial claim with conviction, contrasting two different approaches to evidence and emphasizing a lack of progress in one area
2 Speaker1 and Speaker2 begin with differing opinions, but maintain a civil tone. Speaker2 attempts to clarify Speaker1’s position with a question. Speaker1 responds by elaborating on their stance, providing examples and justifications. Speaker1 aims to clarify their position by providing examples. The conversation remains relatively calm and focused on understanding each other’s perspectives.	<ol style="list-style-type: none"> 1. Speaker1 and Speaker2 begin with differing opinions, but maintain a civil tone 2. Speaker2 attempts to clarify Speaker1 position with a question 3. Speaker1 responds by elaborating on their stance, providing examples and justifications 4. Speaker1 aims to clarify their position by providing examples 5. The conversation remains relatively calm and focused on understanding each other perspective
3 Speaker2 initiates the conversation by recommending a segment. Speaker1 expresses a desire for a concise summary, prompting Speaker2 to claim that a summary would be insufficient. Speaker2 then expresses a negative opinion, using subjective language. Speaker1 responds with agreement and expands on the negative sentiments, while also noting agreement with the underlying message. The overall tone is polite and agreeable.	<ol style="list-style-type: none"> 1. Speaker2 initiates the conversation by recommending a segment 2. Speaker1 expresses a desire for a concise summary 3. Speaker2 claims that a summary would be insufficient 4. Speaker2 expresses a negative opinion, using subjective language 5. Speaker1 responds with agreement 6. Speaker1 expands on the negative sentiments 7. Speaker1 notes agreement with the underlying message

Table 3: Example SCD and SoP representations of three conversations. Conversation 2 (colored in blue) is a similar conversation (positive) of Conversation 1 (ConDynS assign score of 0.544). Conversation 3 (colored in red) is a non-similar conversation (negative) of Conversation 1 (score of 0.112). See Figure 8, 9, and 10 for the entire transcript of each conversation.

C.3 Topic setting during simulation

We first need to identify the topic of the anchor conversation to run a topic sensitivity analysis. We prompt a model to identify the topic of a conversation-pair, as we have a paired dataset (Hua et al., 2024), whose pairs have the same topic. The prompt is provided in Figure 15.

For the *same topic* setting, the topic identified for an anchor conversation is used as the imposed topic to simulate its positive and negative counterparts. For the *different topic* setting, topics identified from the 50 conversations in the dataset are first shuffled. Each anchor is then assigned one of these shuffled topics, which serves as the specified topic for simulating its positive and negative counterparts, while

ensuring that the shuffle topic is different from the anchor’s original identified topic. For the *adversarial* setting, a topic obtained through the shuffling process described in the *different topic* setting is used for simulating the positive counterpart, while the anchor’s original identified topic is used for simulating the negative counterpart.

D Additional Validation Results

We validated our measure using OpenAI’s gpt-4o model (Achiam et al., 2024) as well. We also ran all baseline using gpt-4o generated SCDs. The result is summarized in Table 4.

Measure Representation	ConDynS		cosine sim.	BERTScore	Naive Prompting
	SoP+Trx	SoP	SCD	SCD	SCD
same topic	92%	82%	72%	70%	70%
different topic	98%	74%	76%	66%	64%
adversarial	96%	72%	64%	70%	60%

Table 4: Accuracy of each measure in our validation setup using gpt-4o. The accuracy of baseline is when using gpt-4o’s generated SCD as its input.

E Qualitative Examples

Table 5 includes multiple examples of identified patterns in each cluster.

F Additional Applications Results

Figure 16 demonstrates the intra-group similarity between set Δ and set $\neg\Delta$, as described in Section 6.1

G Miscellaneous

G.1 Data Anonymization

We used the CMV dataset, which we accessed through ConvoKit 3.0.1. The dataset includes the usernames of the conversations participants, which we replace with ‘Speaker1’, ‘Speaker2’, and etc. to respect the users’ identity, following the procedures outlined in Hua et al. (2024).

G.2 Implementation Details

During all generation with Gemini Flash 2.0 via Google Cloud’s Vertex AI API, the sampling temperature was set to 0 for deterministic behaviors, and the reported results are from those single runs. All other settings and parameters were set to the default value. For gpt-4o models, number of output tokens were limited to 512.

G.3 Used Artifacts

The following is a list of artifacts and their licenses used in the work:

- ConvoKit 3.0.1:
<https://convokit.cornell.edu/>, MIT License
- Gemini Flash 2.0: Accessible via Google’s Vertex AI API <https://cloud.google.com/vertex-ai?hl=en>
- gpt-4o-mini-2024-07-18:
a snapshot of gpt-4o-mini from July 18th, 2024. Accessible at a low cost via

OpenAI’s API <https://platform.openai.com/docs/>

- gpt-4o-2024-11-20:
a snapshot of gpt-4o from November 11th, 2024. Accessible via OpenAI’s API <https://platform.openai.com/docs/>
- chatgpt-4o-latest:
most updated version gpt-4o. Accessed on March 2025 via OpenAI’s API <https://platform.openai.com/docs/>
- Sentence Transformers 3.0.0:
<https://github.com/UKPLab/sentence-transformers>, Apache License 2.0
- DistilBERT base model:
Distilled version of BERT accessed through huggingface API <https://huggingface.co/distilbert/distilbert-base-uncased>, Apache License 2.0

Write a short summary capturing the trajectory of an online conversation.

Do not include specific topics, claims, or arguments from the conversation. The style you should avoid:

Example Sentence 1: “SPK1, who is Asian, defended Asians and pointed out that a study found that whites, Hispanics, and blacks were accepted into universities in that order, with Asians being accepted the least. SPK2 acknowledged that Asians have high household income, but argued that this could be a plausible explanation for the study’s findings. SPK1 disagreed and stated that the study did not take wealth into consideration.”

This style mentions specific claims and topics, which are not needed.

Instead, do include indicators of sentiments (e.g., sarcasm, passive-aggressive, polite, frustration, attack, blame), individual intentions (e.g., agreement, disagreement, persistent-agreement, persistent-disagreement, rebuttal, defense, concession, confusion, clarification, neutral, accusation), and conversational strategies (if any) such as “rhetorical questions”, “straw man fallacy”, “identify fallacies”, and “appealing to emotions.”

The following sentences demonstrate the style you should follow:

Example Sentence 2: “Both speakers have differing opinions and appeared defensive. SPK1 attacks SPK2 by diminishing the importance of his argument and SPK2 blames SPK1 for using profane words. Both speakers accuse each other of being overly judgemental of their personal qualities rather than arguments.”

Example Sentence 3: “The two speakers refuted each other with back and forth accusations. Throughout the conversation, they kept harshly fault-finding with overly critical viewpoints, creating an intense and inefficient discussion.”

Example Sentence 4: “SPK1 attacks SPK2 by questioning the relevance of his premise and SPK2 blames SPK1 for using profane words. Both speakers accuse each other of being overly judgemental of their personal qualities rather than arguments.”

Overall, the trajectory summary should capture the key moments where the tension of the conversation notably changes. Here is an example of a complete trajectory summary:

Trajectory Summary:

Multiple users discuss minimum wage. Four speakers express their different points of view subsequently, building off of each other’s arguments. SPK1 disagrees with a specific point from SPK2’s argument, triggering SPK2 to contradict SPK1 in response. Then, Speaker3 jumps into the conversation to support SPK1’s argument, which leads SPK2 to adamantly defend their argument. SPK2 then quotes a deleted comment, giving an extensive counterargument. The overall tone remains civil.

Now, provide the trajectory summary for the following conversation.

Conversation Transcript:

Here is a trajectory summary of a conversation that lays out how the dynamics of the conversation developed. You need to parse the summary into events in order.

Follow the following guidelines:

1. Try to maintain the original language of the summary as much as you can.

2. Provide your output as a Python dictionary with the following structure:

(Note: Do NOT use markdown, JSON formatting, or code block delimiters.)

```
{
  '0': "" // description of the event '1': ""
  ...
}
```

Here is the summary:

Figure 6: Prompt for parsing a SCD into sequence of patterns (SoP).

Figure 5: Procedural prompt for generating SCD (Hua et al., 2024)

You will be given a transcript and a list of events describing conversational dynamic and trajectories. You are tasked with determining how closely a predefined sequence of dynamics is seen in a provided conversation transcript, both in occurrence and order.

Input: - The sequence of events is provided as a dictionary, where: - Keys: indicate the order of events, starting from '0'. - Values: describe each event.

Task: - Analysis: Analyze how closely a given transcript follows the sequence of described events. Think and analyze whether you see any part of the transcript resembles the event. Remember that the sequence of events also has to be considered.

- Similarity Score: Give a float score ranging from 0 to 1 based on your assessment of how closely the description of the traject.

- Order Penalty: If an event occurs before previous events (according to sequence keys), it should be scored significantly lower.

- Proximity of Events: Events in the transcript should closely follow the described sequence. If there are many unrelated events or long gaps between key events, the score should be penalized accordingly.

- Speaker Independence: The event can occur between any speakers, and the actual speaker names do not affect the analysis.

- **Example:**

- 0: No part of the transcript matches the described event at all.

- 0.35: A part resembles the described event but it occurred couple utterances after the previous bullet point event.

- 0.6: A part resembles the described event.

- 1: A part exactly matches the described event explicitly and occurred either at the very first utterance or right after the previous event.

Output Format: Provide your output as a Python dictionary with the following structure:

(Note: Do NOT use markdown, JSON formatting, or code block delimiters.)

'0': 'analysis': 'ANALYSIS (<=20 words)', 'score': i (0 <= i <= 1), '1':

Figure 7: Prompt for scoring each pattern in a SoP against a transcript

SPEAKER1: There's really no easier way of putting it. Can you really expect me to believe people that have these instances where "oh my friend and I..." or "oh I saw it but umm nobody else what there!" C'mon now. Seriously? Why would you believe anything without evidence?

Why? Like...why. I just don't get it. I'm not sure I understand the reasoning behind trying to scare other people and stuff. And those who get spooked are just as lame. I slept in 2 "haunted" houses by myself just to prove a point (and also for money from a bet!) and nothing happened. And yes, I recorded the whole thing with a GoPro. I went to sleep, nothing happened. Nothing strange has ever happened to me and I've been to numerous places where there's been "reported sightings!!!" (o0o0o0o0o0o0o0 so scary).

I'm just sick of all these people claiming this stuff for attention or letting their minds play tricks on them. I bet all of them haven't even gotten enough sleep either.

EDIT: Look what I found! [hyperlink]

> *This is a footnote from the CMV moderators. We'd like to remind you of a couple of things. Firstly, please*
[read through our rules]([hyperlink]). *If you see a comment that has broken one, it is more effective to report it than downvote it. Speaking of which,* ***[downvotes don't change views]([hyperlink])***! Any questions or concerns? Feel free to* ***[message us]([hyperlink]). *Happy CMVing!*

SPEAKER2: You're basically arguing that the people who claim to have seen something when nobody else is around was lying. Right? Or do you think that there is simply a logical explanation for what they claim to have seen? I doubt people would just outright lie about an experience like that.

Near-Death Experiences are a great example. We know they are definitely real now, but had we carried this attitude of "why should we believe this happened to you", then we would have missed out on an incredibly fascinating field of scientific study.

SPEAKER1: I think there's a logical explanation, and that it doesn't involve "ghosts" and is more inline with our brain chemistry and such. Essentially different parts of our brain doing varying things, be they in error or not.

Look at sleep paralysis. That's cause for waking hallucinations - and we understand it and can explain it.

SPEAKER2: Ok but this sentence from your OP

>;why would you believe anything without evidence?

is promoting a very different belief from what you just said here. The quoted statement makes it sound like you think these people made it all up. If their brain chemistry made them see something, then that IS an authentic experience; we just called it something inaccurate.

This is important because if we think it's just all baloney, we would never study it further.

>Look at sleep paralysis. That's cause for waking hallucinations - and we understand it and can explain it.

And we never would have figured this out if we approached a statement like "I saw you walk across the room while I was sleeping" with a statement like "why would we believe anything like this without evidence?"

SPEAKER1: Allow me to reiterate: Ghosts do not exist.

While some have tried to prove they have, nothing happened to our benefit.

We also have discovered much else because of the same approach. It has been tried to be proven, but failed. Sleep paralysis was a confirmed thing that we kept looking into, just like ghosts. Except one is now much further because of the thread of evidence that we had in the first place. The other doesn't.

Figure 8: Full transcript of Example Conversation 1

SPEAKER1: To say Player Unknown's Battle Grounds (PUBG) and Fortnite Battle Royal (Fortnite) have gotten huge is a vast understatement. PUBG first dominated the scene earlier this year by being a definitive addition to the genre, then Fortnite stole the limelight by addressing the problems (mainly developer integrity and system performance) PUBG had. Both are still going strong with their own audiences, art styles, design choices, and most importantly, eSports leagues. Big name teams like Cloud9 and Natus Vincere are hopping on board PUBG's league, and Fortnite's publisher, Epic Games, announced their 100 million contribution to prize pools for competitions for the next year.

I think it's all bullshit.

Any game in the battle royal genre is inherently unbalanced. RNG luck is too big of a factor in these games, making every game unfair regardless of the circumstances. Where you can drop at the beginning of the match, who's sitting next to you on the plane, what guns will be on the ground waiting for you, and when/where the supply drops are, are all random. Success in the game is determined more by luck than skill there's nothing that even best player can do when they finally land only to be blasted in the face by someone else with the shotgun that just so happened to be closer to them.

This brings me to my other point on it's effect on the eSports scene. The games that have defined eSports CounterStrike, DoTa 2, League of Legends, etc. draw many parallels to physical sports. They require skills that can be practiced, and can benefit from strategies, techniques, and teamwork, similar to a real sport. I have a phrase that I've been waiting to say to someone that says otherwise: "This isn't competitive Candy Crush." I've argued against people that try to overgeneralize video games as "sitting on their ass hitting buttons," overlooking the mechanical skills and knowledge of the game required to do well. I fear that if PUBG and Fortnite takes off in a competitive sense, the amount of luck present in the game will undermine the games I listed earlier those built from the ground up to give players a level playing field as being easier than they are.

eSports is a well-established industry at this point, and to say it's here to stay should be a given. But with the notion of the BR genre making it's presence known, I do have my concerns on how people think about eSports as a whole. Edit: I should probably clarify, my point on RNG in the BR genre is that RNG is *too far embedded* into the games to make it competitive, and not enough of it can be mitigated to make things a fair fight. RNG is fine in other games, so long as they can be mitigated.

I should also clarify that when I say RNG, I mean a true Random Number Generator. Variances from other sources I have no problem with.

SPEAKER2: PUBG is definitely not eSports ready but not because of the core RNG mechanic of the game. Every sport or game has factors outside of the player's control, and part of being a good competitor is being able to prepare and react to it. As long as the RNG component can't be hacked or manipulated then it is fair by definition. It may be merely that the structure of the competition needs to take into consideration the RNG element, for example a PUBG tournament should be based on several matches and not just single elimination so that player skill has a chance to shine.

SPEAKER1: I understand there are factors outside of the player's control in any activity. Having some of these factors being decided by a computer is what I'm against. If some of these factors can at least be mitigated (eg, rain at an event can be fixed by a stadium with a roof, weapon spread can be disabled server-side), then I'm okay with it, but shooting someone's head and missing because a computer decided I don't get to kill someone today is infuriating, and in my opinion not fun to watch.

SPEAKER2: > but shooting someone's head and missing because a computer decided I don't get to kill
So do you have a problem with Battle Royal games or just with the gun mechanics? Overwatch has RNG bullet spread too though obviously more consistent.

SPEAKER1: I have a problem with the RNG that's in both. The RNG that determines gun inaccuracy, as well as the RNG that determines which plane you're on and what/where weapons/boxes will spawn.

I'm a bit rusty on Overwatch, the only hit-scans I can think of that have spread would be Soldier 76, Tracer, McCree's "Fan the Hammer," Roadhog, and Reaper.

Tracer, Roadhog, and Reaper, and McCree's FtH are meant to be used up close, where RNG doesn't matter.

McCree's basic attack is 100 amp;37; accurate with a slow rate of fire, which brings me to Soldier 76. His bloom can be worked around by simply bursting/tapping his rifle, which I'm fine with.

In games with weapon inaccuracy, what makes a player skilled is his ability to circumvent/mitigate the inaccuracy. In CS:GO, where moving makes your gun shoot everywhere on your screen, movement comes with several options to mitigate movement inaccuracy (like counter strafing).

Figure 9: Full transcript of Example Conversation 2

hyperlink: I've been a member for a year, ever since I began educating myself about firearms, took extensive training, and bought three. I've now also passed enhanced background checks and earned concealed carry permits in three states.

I haven't seen any news items with good arguments against the NRA that hold up on scrutiny. Every article I see is, "ignore what they're saying; here's what they really mean". You can imagine how that's unconvincing.

Plus, the latest CNN (?) town square with students, Dana Loesch and politicians was the worst of mob theater. Nothing there for me but confirmation in my beliefs.

As an organization for its members, I like everything the NRA does: they change with the times [sponsoring great vloggers like Colion Noir]([hyperlink]), offering insurance and legal help, and supporting victims of gov't gun confiscation. [Example video]([hyperlink]), [case info]([hyperlink]).

About me: I'm a member of both the NRA and PETA. I'm politically moderate, After decades believing the "conventional wisdom" about these and other groups, I started deep diving into the supporting facts behind the frequent hit pieces about them. And I found that most (all?) fall apart under scrutiny.

> *This is a footnote from the CMV moderators. We'd like to remind you of a couple of things. Firstly, please*
 [read through our rules]([hyperlink]). *If you see a comment that has broken one, it is more effective to report it than downvote it. Speaking of which,* ***[downvotes don't change views]([hyperlink])***! Any questions or concerns? Feel free to* ***[message us]([hyperlink])***. *Happy CMVing!*

SPEAKER2: Watch the enost recent segment John Oliver did on them. It's pretty interesting.

SPEAKER1: Thanks - could you sum it up in a sentence or two?

SPEAKER2: Not well enough. It's like twenty minutes. One good thing to notice about them though is that they are no different than an infomercial channel. They profit off of their beliefs which is why their ads-IMO- are so cringey with their intenseness. I stopped following gun channels on YouTube who ran their ads. Don't regret it.

SPEAKER1: I'm also not a fan of their videos (or any) with the threatening soundtrack, etc. Also the excessive branding and intro screens. Yeah, I avoid those. I pretty much always agree with the message, though.

Figure 10: Full transcript of Example Conversation 3

Compare the following two online conversations and rate their similarity on a scale from 1 to 100, based on their trajectory.

Definition of Trajectory

The trajectory of a conversation refers to its dynamics, including:

- **Changes in tone** (e.g., neutral to argumentative, formal to casual, sarcastic or sincere).
- **Patterns of interaction** (e.g., back-and-forth exchanges, long monologues, interruptions).
- **Conversation strategies** (e.g., persuasion, questioning, storytelling).
- **Order of the above trajectory events**

Ignore:

- The topics discussed.
- Specific factual content.

Output Requirements

Return a JSON object containing:

- "sim_score" (int): A similarity score between 1–100, representing how similar the conversations are in trajectory.
- "reason" (string, <=30 words): A brief explanation of why the score was given, referencing key conversational dynamics.

Output Format (JSON)

```
{
  sim_score: int,
  reason: brief explanation under 30 words
}
```

Conversations

Conversation 1:

Conversation 2:

Figure 11: Prompt for naive prompting baseline

Compare the following two summary of conversation dynamics (SCD) of two online conversations, rate the similarity of the two conversations on a scale from 1 to 100, based on their persuasion trajectory reflected in the SCDs.

Definition of Trajectory
The trajectory of a conversation refers to its dynamics, including:

- **Changes in tone** (e.g., neutral to argumentative, formal to casual, sarcastic or sincere).
- **Patterns of interaction** (e.g., back-and-forth exchanges, long monologues, interruptions).
- **Conversation strategies** (e.g., persuasion, questioning, storytelling).
- **Order of the above trajectory events**

Ignore:

- The topics discussed.
- Specific factual content.

Output Requirements
Return a JSON object containing:

- "sim_score" (int): A similarity score between 1–100, representing how similar the conversations are in **trajectory** based on the SCDs.
- "reason" (string, <=30 words): A brief explanation of why the score was given, referencing key conversational dynamics.

Output Format (JSON)

```
{  
  sim_score: int,  
  reason: brief explanation under 30 words  
}
```

Conversations
Conversation 1 SCD:
Conversation 2 SCD:

Figure 12: Prompt for naive prompting baseline with SCDs

#	Category	Dynamics	Examples
1	Tone	negative politeness (gratitude, thanks, appreciation)	SPK1 expresses gratitude for the validating response. SPK1 expresses empathy and appreciation for SPK2 insight.
		collaborative (collaborative, build upon)	SPK1 and SPK2 build upon each other point. The conversation maintains a collaborative sentiment throughout.
		conciliatory (acknowledgement, acknowledges, apologizing)	SPK1 acknowledges new information. SPK1 apologizes for misunderstanding and offers a polite suggestion for future communication
	Strategy	elaboration (specific, detailed, information, informative)	SPK2 introduces information SPK2 begins by providing a detailed and informative response, seemingly intending to persuade SPK1.
		agreement (agrees, agreement, validate)	SPK1 expresses agreement and appreciation. SPK2 attempts to validate SPK1 concerns.
		compromise (compromise, concedes, concession)	SPK2 offers a revised premise. SPK1 initially agrees with SPK2 point but expresses a reservation, seeking a compromise.
	Changes	changes in perspective (revised, change)	SPK2 offers a revised premise. SPK1 then conceded, acknowledging the validity of SPK2 point and expressing a change in perspective.
		shift to lighter tone	SPK2 shifts to a more agreeable tone. SPK1 shifts the tone from serious concern to a more humorous outlook.
2	Tone	dismissive (frustrated, dismissive)	SPK2 begins by disagreeing... using a dismissive tone. SPK2, maintaining a dismissive and sarcastic tone, expresses persistent disagreement.
		sarcastic (sarcasm, sarcastically)	SPK2 begins with a rhetorical question, seemingly sarcastic. SPK2 responds with sarcasm and attempts to clarify the definition of a term used by SPK1.
		defensive (defensive, resists)	SPK1 expresses defensiveness. SPK1 responds defensively, limiting the scope of the discussion and questioning SPK2 reasoning.
		confrontational (accuses, blame, confrontational)	SPK1 maintains a confrontational stance. SPK2 accuses SPK1 of using a straw man fallacy.
	Strategy	straw man fallacy (straw man)	SPK2 uses a sarcastic tone and straw man fallacy. SPK1 then uses a straw man fallacy, misrepresenting SPK2 argument to attack it.
		philosophical argument (philosophical argument/concept/difference)	SPK1 responds with a philosophical argument. SPK2 defends their position, identifying what they believe is a core philosophical difference with SPK1.
		providing examples (examples, example)	SPK2 attempts to clarify their position using examples. SPK1 continues to disagree, providing counter-examples and expressing skepticism.
		analogy (analogy, analogies, hypothetical)	SPK2 initiates the conversation with a hypothetical scenario. SPK1 accuses SPK2 of not taking the conversation seriously, while also clarifying their stance.
		seeking clarification (confusion, lack of understanding, seeking clarification)	SPK2 initially expresses confusion and seeks clarification. SPK1 expresses confusion and disagreement with SPK2 premise.
		disagreement (disagrees, disagreement, contrasting)	SPK2 quickly introduces a contrasting viewpoint. SPK1 immediately expresses disagreement with the definition.
		direct responses (direct, directly, immediately, quickly)	SPK1 immediately disagrees, using statistics to justify . SPK2 directly disagrees with SPK1, asserting a factual error and expressing shock.
	Changes	maintains perspective (continues, maintains strong negative, persists)	SPK1 maintains a negative tone towards specific actors. SPK1 continues to disagree, using another analogy to defend their position.
		shift to contentious tone	SPK1 shifts from concession to disagreement. SPK1 shifts to a more accusatory tone, implying a lack of justification.

Table 5: Qualitative analysis of the two identified clusters. Dynamics found in Cluster 1 are on the top; dynamics found in Cluster 2 are on the bottom. Phrases in parentheses are distinguishing words used during the analysis.

You are given a task to recreate an online conversation that occurred on reddit. Here is a list of information you are given.

1. Topic of the conversation: {topic}
2. The original conversation that which the conversation trajectory you should follow: {transcript}

Definition of Trajectory The trajectory of a conversation refers to its **dynamics**, including:

- **Changes in tone** (e.g., neutral to argumentative, formal to casual, sarcastic or sincere).
- **Patterns of interaction** (e.g., back-and-forth exchanges, long monologues, interruptions).
- **Conversation strategies** (e.g., persuasion, questioning, storytelling).
- **Order of the above trajectory events**

Ignore:

- The topics discussed.
- Specific factual content.

In your recreated conversation, each utterance of the transcript should be formatted as the following:
 Speaker_ID (e.g. "SPK2") :

#Output Add your recreated conversation. Only generate the transcript of the conversation.

Figure 13: Prompt for simulating conversation with transcript

You are given a task to recreate an online conversation that occurred on reddit. Here is a list of information you are given.

1. Topic of the conversation: {topic}
2. Trajectory summary that summarizes the conversational and speakers' dynamics: {trajectory_summary}

Each utterance of the transcript should be formatted as the following:
 Speaker_ID (e.g. "SPK2") : Add text of the utterance

#Output Add your recreated conversation. Only generate the transcript of the conversation.

Figure 14: Prompt for simulating conversation

Here are two conversations of the same topic. Summarize the topic of the conversations in a concise phrase that accurately captures the main subject being discussed.

Here is the transcript of the first conversation:
 {transcript1}

Here is the transcript of the second conversation:
 {transcript2}

Now, write the topic of the conversation in a concise phrase:

Figure 15: Prompt for identifying the topic of the conversation.

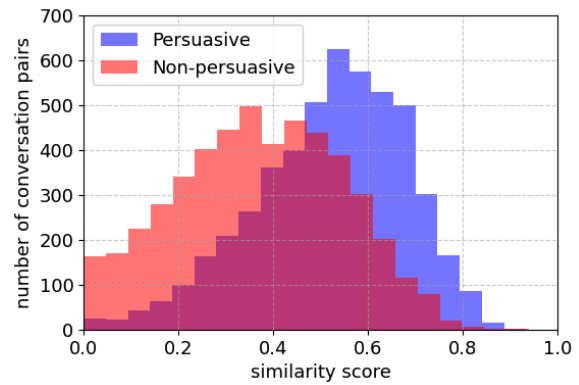


Figure 16: Distribution of similarity scores computed using ConDynS for conversations within set Δ (blue) and within set $\neg\Delta$ (red).