Probing Discourse Structure in Dialogue: Evaluating and Fine-Tuning RoBERTa and BART on Sentence Ordering and Next Sentence Prediction

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Abstract

This study investigates how large language models represent discourse structure in dialogue through two probing tasks: sentence ordering and next sentence prediction (NSP). Using the STAC corpus of multi-party conversational data, RoBERTa and BART are evaluated in both pre-trained and fine-tuned settings. Fine-tuning yields substantial gains across both tasks, with BART's generative architecture proving more effective for sentence ordering ($\rho = 0.473$) while RoBERTa excels at NSP classification (accuracy = 0.697). Focusing on four core discourse relations, the analysis finds that models handle frequent, surface-cued relations (Question-Answer Pairs, Comment) effectively but struggle with relations requiring deeper semantic dependencies (Continuation, Elaboration). These findings highlight both the capabilities and limitations of current models in capturing discourse-level coherence in dialogue.

1 Introduction

Large language models (LLMs) have revolutionized natural language processing but face challenges in capturing discourse-level coherence in dialogue (Holtzman et al., 2020). While excelling at surface-level language tasks, their ability to maintain logical flow across multi-turn conversations remains limited. This work extends the probing framework of (Koto et al., 2021) from monologic texts to dialogue, evaluating discourse coherence through sentence ordering and next sentence prediction (NSP) tasks.

The contributions are threefold: (1) demonstrating the necessity of fine-tuning for dialogue discourse understanding, (2) revealing architectural strengths—BART for generation, RoBERTa for classification, and (3) providing focused relation-specific analysis on four core discourse relations showing that models excel at surface-cued relations but struggle with semantic dependencies. Using the STAC corpus (Asher et al., 2016) with Segmented Discourse Representation Theory (SDRT) annotations (Asher and Lascarides, 2003), this research offers insights into discourse modeling capabilities of transformer architectures (Vaswani et al., 2017).

2 Related Work

2.1 Discourse Structure and Dialogue

Discourse coherence frameworks like SDRT (Asher and Lascarides, 2003) model conversations through relations between Elementary Discourse Units (EDUs). While resources like RST Discourse Treebank (Carlson et al., 2001) and Penn Discourse Treebank (Prasad et al., 2008) focus on written texts, the STAC corpus (Asher et al., 2016) provides fine-grained discourse annotations for multi-party game dialogues, capturing strategic conversations with non-linear discourse links essential for probing dialogue coherence.

2.2 Probing Language Models

(Koto et al., 2021) established probing tasks including sentence ordering and NSP to evaluate discourse awareness, finding RoBERTa and BART most sensitive to discourse phenomena. However, their study focused on monologic texts, leaving dialogue coherence unexplored. This work extends this approach to conversational data with focused relation-specific evaluation on four core discourse relations.

2.3 Sentence Ordering and NSP

Sentence ordering serves as a coherence proxy (Barzilay and Lapata, 2008), with neural approaches demonstrating pattern recognition (Logeswaran et al., 2018; Gong et al., 2016). BART's sentence permutation pre-training (Lewis et al., 2020) aligns naturally with this task, while RoBERTa's contextual representations (Liu et al.,

2019) suit ranking approaches. NSP, though questioned for pre-training utility (Liu et al., 2019), remains valuable for probing local coherence and has been used in dialogue response selection (Zhang et al., 2018; Whang et al., 2020).

2.4 Differences from Previous Work

This study differs from (Koto et al., 2021) in three key aspects: (1) focusing on dialogue rather than monologic texts, (2) employing relation-specific analysis across discourse types, and (3) comparing architectural preferences across generative and discriminative paradigms. Unlike dialogue response selection studies (Zhang et al., 2018; Whang et al., 2020), this work probes inherent discourse understanding rather than response generation performance.

3 Methodology

3.1 Dataset and Tasks

The STAC corpus (Asher et al., 2016) contains multi-party online game dialogues annotated with SDRT relations. After preprocessing — including cleaning malformed text, handling token limits, and segmenting utterances into Elementary Discourse Units (EDUs) — dialogues with fewer than three EDUs were excluded to ensure meaningful evaluation of ordering. The study uses two probing tasks:

Sentence Ordering: Models reconstruct the original EDU sequence from shuffled input. The task is evaluated by Spearman's ρ, calculated after aligning predicted EDU sequences to gold sequences using the Ratcliff–Obershelp algorithm (Ratcliff and Obershelp, 1988), considering only overlapping units.

Next Sentence Prediction: A binary classification task on pairs of EDUs. Positive pairs are adjacent EDUs connected by a discourse relation; negative pairs are non-adjacent EDUs. Balanced accuracy is used to account for class distribution across relation types.

The analysis focuses on four discourse relations with substantial data support: Question-Answer Pair, Comment, Continuation, and Elaboration.

3.2 Models and Evaluation

BART (Lewis et al., 2020): Encoder-decoder fine-tuned for sequence generation (sentence ordering) and binary classification (NSP).

RoBERTa (Liu et al., 2019): Encoder-only model used for reranking (sentence ordering) and classification (NSP).

Both models were fine-tuned using standard hyperparameters with relation-aware special tokens. Specifically, relation-type tokens (e.g., `[REL:QAP]`, `[REL:CONT]`) were prepended to each EDU to make discourse relations explicit in the input. Evaluation uses Spearman's ρ for sentence ordering and balanced accuracy for NSP. Statistical significance of improvements was tested using paired Wilcoxon signed-rank tests (Wilcoxon, 1945), with confidence intervals reported via bootstrap resampling (Cumming, 2014).

3.3 Experimental Setup

Fine-tuning used consistent hyperparameters across both models (Table 1): learning rate of 2e5, batch size 16, and 3 epochs. Data splits included cross-validation (sentence ordering) and 80/10/10 splits (NSP). All splits were performed at the dialogue level to ensure that EDUs from the same dialogue do not appear in both training and test sets, preventing data leakage. Relation-aware special tokens were added during tokenization. BART ordering used beam search (size 5) with Ratcliff–Obershelp alignment; RoBERTa reranking evaluated 6 permutations per dialogue (inputs truncated to 512 tokens). All runs used early stopping (patience 2) and a fixed random seed.

Table 1: Hyperparameter settings for fine-tuning experiments.

Parameter	BART	RoBERTa
Learning rate	2e-5	2e-5
Batch size	16	16
Training epochs	3	3
Warmup steps	500	500
Weight decay	0.01	0.01
Max sequence length	512	512

4 Results

4.1 Overall Performance

Fine-tuning yields substantial improvements across both tasks (Table 2). For sentence ordering, BART achieves $\rho = 0.473$ (vs. 0.130 baseline) while RoBERTa reaches $\rho = 0.467$ (vs. 0.149 baseline). For NSP, RoBERTa achieves higher accuracy (0.697) than BART (0.637), reflecting architectural advantages for classification tasks.

All improvements are statistically significant ($p < 0.001$).

Table 2: Overall performance across tasks and models. SO: Sentence Ordering (ρ), NSP: Next Sentence Prediction (accuracy). Scores are means over test instances. All improvements from fine-tuning are statistically significant ($p < .001$, paired Wilcoxon signed-rank tests). Confidence intervals for the improvements are provided in Section 4.1.1.

Task	Model	n	Base.	Fine.
SO	BART	712	0.130	0.473
	RoBERTa	188	0.149	0.467
NSP	BART	1,776	0.499	0.637
	RoBERTa	293	0.510	0.697

4.1.1 Statistical Analysis of Improvements

The effects of fine-tuning were quantified using mean gains (Δ) with 95% confidence intervals (CIs) derived from paired bootstrap resampling (10,000 iterations). For sentence ordering, BART shows $\Delta\rho = 0.343$ (95% CI: [0.309, 0.377]), while RoBERTa shows $\Delta\rho = 0.318$ (95% CI: [0.201, 0.434]). For NSP, the gains are $\Delta\text{acc} = 0.137$ (95% CI: [0.105, 0.171]) for BART and $\Delta\text{acc} = 0.187$ (95% CI: [0.155, 0.219]) for RoBERTa. All fine-tuned models perform significantly above chance level (one-sided Wilcoxon test: $p < .001$ for $\rho > 0$ or acc > 0.5). Complete results for all 15 discourse relations analyzed (including Acknowledgement, Explanation, and Contrast) are consistent with this pattern and are provided in the supplementary material. All experiments used a fixed random seed, with results based on single runs and statistics aggregated over the test set.

4.2 Relation-Specific Analysis

Performance is analyzed across four core discourse relations to understand model capabilities at different levels of discourse complexity (Table 3).

Question-Answer Pairs show the strongest performance across both tasks, with both models achieving high scores in ordering and NSP. **Comment** relations demonstrate solid performance in sentence ordering but more modest gains in NSP. **Continuation** proves challenging for BART in ordering but both models handle it well in NSP. **Elaboration** shows the largest architecture-dependent variation, with RoBERTa substantially outperforming BART in NSP.

Table 3: Performance by discourse relation type (fine-tuned models). Values are mean scores over test instances. Confidence intervals and full statistical details are available upon request.

Relation	Sentence Ordering (ρ)		NSP (Accuracy)	
	BART	RoBERTa	BART	RoBERTa
Question-Answer	0.498	0.487	0.675	0.701
Comment	0.450	0.431	0.544	0.630
Continuation	0.384	0.552	0.678	0.699
Elaboration	0.395	0.342	0.548	0.691

5 Discussion

5.1 Discourse Awareness Through Fine-Tuning

The significant performance gap between baseline and fine-tuned models demonstrates that pretraining alone is insufficient for reliable discourse coherence modeling. While pretrained models show basic syntactic and semantic knowledge, domain-specific fine-tuning is essential for capturing dialogue-specific discourse patterns, particularly for the four focal relations.

5.2 Architectural Alignment with Task Demands

The results reveal clear architectural preferences: RoBERTa's encoder-only design excels at classification tasks (NSP), while BART's encoder-decoder framework benefits generation tasks (sentence ordering). This pattern is most pronounced for Elaboration relations, where RoBERTa achieves 0.691 NSP accuracy compared to BART's 0.548, suggesting RoBERTa's discriminative approach better captures semantic dependencies.

5.3 Relation-Specific Capabilities and Limitations

The focused analysis reveals a clear hierarchy of model capabilities across the four relations:

Question-Answer Pairs represent the most accessible relation type, benefiting from strong adjacency patterns and lexical complementarity within the game negotiation context. Models reliably learn to preserve question-response sequences after fine-tuning.

Comment relations show intermediate performance, with models successfully grouping related evaluative utterances but sometimes failing to capture pragmatic ordering conventions.

Continuation exposes limitations in tracking

procedural logic across turns. While models identify related terms in negotiations, they often break the sequence of proposals and counteroffers, indicating reliance on lexical coherence over logical flow.

Elaboration demonstrates the potential for learning semantic dependencies, particularly with RoBERTa's strong NSP performance. However, the relation remains challenging for sentence ordering, suggesting difficulties with global coherence modeling.

5.4 Error Analysis and Case Studies

Qualitative analysis reveals systematic error patterns. The following examples illustrate how models, particularly BART, can confuse *Continuation* (a sequential, procedural relation) with *Elaboration* (a semantic dependency relation) due to overlapping lexical cues.

Example 1 (Continuation misidentified as Elaboration):

> *Gold order:* "I need wood." → "I can give you clay for it." → "No, I need wood for a settlement."
> *Predicted order (BART):* "I need wood." → "No, I need wood for a settlement." → "I can give you clay for it."

Here, the model groups the two "need wood" utterances together (treating them as *Elaboration*) and detaches the offer ("clay for it"), breaking the negotiation *Continuation*. The model prioritizes lexical repetition over procedural logic.

Example 2 (Elaboration with spurious causal chain):

> *Gold:* "He stole my sheep." → "That's why I'm attacking next turn."
> *Predicted (BART):* "I'm attacking next turn." → "He stole my sheep."

The model reverses the cause–effect order, placing the action before its explanation, thereby losing the *Elaboration* link. RoBERTa's NSP classifier correctly identifies the true order in this case, reflecting its stronger grasp of semantic dependency.

For *Continuation* relations, models frequently misorder negotiation sequences, placing counteroffers before initial proposals when they share lexical overlap. In *Elaboration* examples, BART often generates plausible but incorrect causal chains, while RoBERTa more reliably identifies true explanatory relationships. A notable failure case involves nested relations, where models correctly handle local coherence but fail to maintain global discourse structure across multiple turns.

5.5 Impact of Input Length Constraints

The 512-token input constraint, particularly for RoBERTa, limited the evaluation to shorter dialogues (n=188 for ordering vs. BART's n=712). This truncation may remove contextual cues necessary for global coherence modeling in longer conversations, potentially underestimating the models' capabilities on relations like Continuation and Elaboration that span multiple turns. Future work should explore long-context architectures or hierarchical encoding to better capture extended dialogue structure.

6 Conclusion

This work extends discourse probing to dialogue through focused analysis of four core relations. The results demonstrate that fine-tuning is essential for discourse coherence modeling and reveal clear architectural preferences: RoBERTa for classification, BART for generation. The relation-specific hierarchy—from easily learned Question-Answer Pairs to challenging Continuation and Elaboration relations—provides a nuanced understanding of current capabilities and limitations. Future research could explore specific hybrid architectures, such as a pipeline where BART generates candidate sequences and RoBERTa reranks them, or incorporate graph neural networks to explicitly model SDRT structures. Additionally, expanding to more diverse dialogue domains beyond game negotiations would test the generalizability of these findings.

Limitations

This study focuses on four discourse relations from the STAC game dialogues, which may limit generalizability to other relation types and domains. The 512-token input constraint particularly affects RoBERTa's sentence ordering evaluation, limiting analysis of longer conversational sequences. Future work should expand to include other dialogue domains and address input length constraints.

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