Uncovering the Potential of ChatGPT for Discourse Analysis in Dialogue: An Empirical Study

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Abstract

Large language models, like ChatGPT, have shown remarkable capability in many downstream tasks, yet their ability to understand discourse structures of dialogues remains less explored, where it requires higher level capabilities of understanding and reasoning. In this paper, we aim to systematically inspect ChatGPT's performance in two discourse analysis tasks: topic segmentation and discourse parsing, focusing on its deep semantic understanding of linear and hierarchical discourse structures underlying dialogue. To instruct ChatGPT to complete these tasks, we initially craft a prompt template consisting of the task description, output format, and structured input. Then, we conduct experiments on four popular topic segmentation datasets and two discourse parsing datasets. The experimental results showcase that ChatGPT demonstrates proficiency in identifying topic structures in general-domain conversations yet struggles considerably in specific-domain conversations. We also found that ChatGPT hardly understands rhetorical structures that are more complex than topic structures. Our deeper investigation indicates that ChatGPT can give more reasonable topic structures than human annotations but only linearly parses the hierarchical rhetorical structures. In addition, we delve into the impact of in-context learning (e.g., chain-of-thought) on ChatGPT and conduct the ablation study on various prompt components, which can provide a research foundation for future work. The code is available at `https://github.com/yxfanSuda/GPTforDDA`.

Keywords: Large Language Model, Dialogue Topic Segmentation, Dialogue Discourse Parsing, Chain-of-Thought

1. Introduction

With the development of generative models, large language models (e.g., ChatGPT) have exhibited remarkable capability on various natural language generation (NLG)(Jiao et al., 2023; Zhang et al., 2023a,b; Yang et al., 2023) and understanding (NLU) (Wei et al., 2023; Yuan et al., 2023; Hu et al., 2023; Gao et al., 2023b) tasks. Despite this progress, there remains an absence of a qualitative and quantitative evaluation of ChatGPT on dialogue discourse analysis. Such an evaluation is vital to uncover the potential of ChatGPT for deep semantic understanding of conversations.

Dialogue discourse analysis plays a crucial role in natural language processing (NLP) by revealing the underlying topic, coherence, and rhetorical structures in a dialogue. Most previous work in this field mainly focuses on dialogue topic segmentation (Lin et al., 2023a; Gao et al., 2023a; Lin et al., 2023b; Xing and Carenini, 2021; Xie et al., 2021) and discourse parsing (Chi and Rudnicky, 2022; Fan et al., 2022; Yu et al., 2022; Wang et al., 2021a; Shi and Huang, 2019), aiming to study the linear topic structures and hierarchical rhetorical structures, respectively, as depicted in Figure 1. Considering ChatGPT as the most recent language generation capability, the potential of its discourse structure understanding proficiency remains largely uncharted. Unlike some NLP tasks that only require a shallow semantic understanding to extract the output from the input, dialogue discourse analysis poses a unique challenge for LLMs, which requires a deeper semantic understanding to derive the latent discourse structures. Therefore, our study delves into the performance of ChatGPT on topic segmentation and discourse parsing to explore the capability of ChatGPT in deep semantic understanding, including linear topic structure and hierarchical rhetorical structure.

To this end, we first crafted the prompt consisting of three components: task description, output format, and structured input. The task description tells ChatGPT what needs to be accomplished, the output format instructs ChatGPT to output in a specified format that can easily extract linear/hierarchical structure for evaluation, and the

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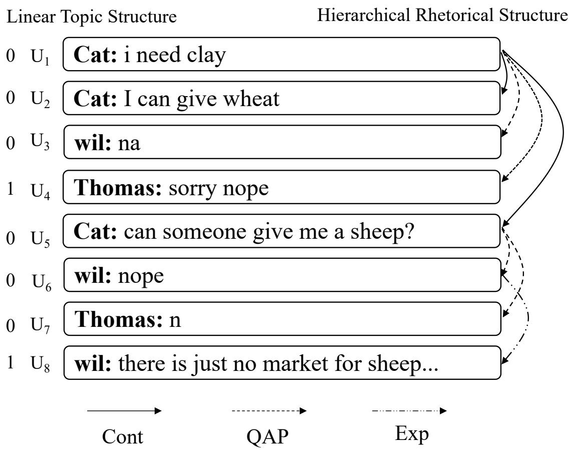


Figure 1: A dialogue from the STAC (Asher et al., 2016) dataset, consisting of seven utterances U_1-U_7 and three speakers *Cat*, *wil*, and *Thomas*. Dialogue topic segmentation aims to reveal the linear topic structure by dividing the dialogue into several topical pieces and '1' indicates the end of a topic. Dialogue discourse parsing aims to reflect hierarchical rhetorical structure by establishing discourse links of utterance pairs according to discourse relations, where *Cont*, *QAP*, and *Exp* is short for *Continuation*, *Question-answer_pair*, and *Explanation*, respectively.

structured input provides ChatGPT with organized content that needs to be analyzed. Then, we conducted two times experiments on four popular topic segmentation datasets and two discourse parsing datasets and reported the average performance.

Experimental results showcased that ChatGPT has a good understanding of linear topic structures in the general domain but struggles to understand the topic structure of the specific domain. Besides, ChatGPT can hardly understand the hierarchical rhetorical structures. In-depth analysis reveals that ChatGPT can give more reasonable topic structures than human annotations but only parses the hierarchical rhetorical structures linearly.

In addition, attempting to enhance the abilities of ChatGPT for deep semantic understanding, we explored the effect of In Context Learning (ICL). The results showcased that ICL could not facilitate ChatGPT to understand linear structures but improve the abilities of ChatGPT to understand hierarchical structures. Notably, the chain-of-thought method of ICL contributes the most.

Furthermore, we conducted ablation experiments to explore the role of various prompt components. The ablation results reveal that the output format plays the most important role. This provides some insights into crafting prompts for studying the dialogue discourse analysis.

Finally, we studied the instruction-following abilities of ChatGPT and found that ChatGPT can not fully follow the instructions on all datasets. This indicates that the robustness of ChatGPT is still an issue of concern.

We hope that our study can provide a solid foundation for the research of dialogue discourse analysis in the future.

2. Related work

2.1. Evaluation of ChatGPT

Recently, some works have evaluated the performance of ChatGPT on a series of downstream tasks, including machine translation (Jiao et al., 2023), summarization (Zhang et al., 2023a; Yang et al., 2023), information extraction (Wei et al., 2023; Han et al., 2023; Yuan et al., 2023; Hu et al., 2023; Gao et al., 2023b), and other NLP tasks (Pu and Demberg, 2023; Susnjak, 2023; Qin et al., 2023). Most of the previous studies explore the capabilities of ChatGPT for shallow semantic understanding that obtaining the output according to the mapping relation between input and output or directly extracting the content from the input. Different from these tasks, dialogue discourse analysis requires ChatGPT to have deeper semantic understanding ability to deduce the discourse structures underlying dialogue.

2.2. Dialogue Topic Segmentation

Previous work on dialogue topic segmentation mainly identifies topic boundaries by studying the local coherence of consecutive utterances, which is divided into two types: unsupervised and supervised. The unsupervised methods (Song et al., 2016; Xu et al., 2021; Xing and Carenini, 2021) mainly first train a coherence model to assess the similarity of consecutive utterances, then a global segmentation algorithm, such as TextTiling (Hearst, 1997), is adopted to identify the topic boundaries. And those supervised approaches (Xie et al., 2021; Lin et al., 2023b,a) mainly adopt sequence labeling to determine the topic boundaries. Different from the previous work with a 0/1 sequences as the output format, we instruct ChatGPT to output the consecutive utterances within the same topic in a dialogue.

2.3. Dialogue Discourse Parsing

Traditional work on dialogue discourse parsing mainly studies the coherence between any two utterances and then adopts a global decoding (e.g., maximum spanning trees) to parse the hierarchical rhetorical structure. The work can be divided into two types, i.e., model augmentation and data augmentation. Those model augmentation (Shi and Huang, 2019; Wang et al., 2021a; Fan et al., 2022; Chi and Rudnicky, 2022) approaches mainly design various sophisticated encoding or decoding methods for discourse parsing. Data augmentation approaches (Yang et al., 2021; He et al., 2021; Liu and Chen, 2021; Yu et al., 2022; Fan et al., 2023) mainly integrate the data of related tasks to facilitate dialogue discourse parsing. Different from the previous work that adopts the adjacency matrix as the output format, we instruct ChatGPT to output the rhetorical structures in the format of a sparse matrix.

3. ChatGPT for Dialogue Discourse Analysis

3.1. Prompt Template Design

The key to evaluating the performance of ChatGPT on specific tasks is to design appropriate prompts (Jiao et al., 2023; Wei et al., 2023; Han et al., 2023). Unlike other tasks, e.g., translation, information extraction, etc., which require a simple task description, guiding ChatGPT in dialogue discourse analysis requires not only the task description but also the output format of discourse structure for evaluation. To this end, we crafted the prompt template consisting of three components: task description, output format, and structured input, as shown in Table 1.

Task Description The task description guides ChatGPT to understand and complete the task as required. For each task, we describe the goal of the task, such as identifying several boundaries for dialogue topic segmentation, to instruct ChatGPT to understand and complete the task.

Output Format The output format instructs ChatGPT to output in a specified format that can easily extract linear/hierarchical structure for evaluation. Specifically, the linear topic structure is output in the format of a Python dictionary, where the key is the topic indication and the value is a list containing the index of consecutive utterances. The hierarchical rhetorical structure is output in the format of a sparse matrix. The Python dictionary and sparse matrix make it simple to extract the linear and hierarchical structures for assessment and analysis.

Structured Input The structured input provides ChatGPT with organized content that needs to be analyzed. We number each utterance in the conversation and feed them into ChatGPT line by line.

3.2. Post-processing

Since ChatGPT is a generative model, the output can not always follow the format specified. For these outputs that do not follow the specified format, we have to conduct post-processing for evaluation.

{'topic 1': [0, 1, 2, 3], 'topic 2': [5, 6, 7, 8]}

↓ Post-processing

[0, 1, 2, 3], [4], [5, 6, 7, 8]

(a) Inter-topic processing.

{topic 1': [0, 1, 2, 3, 5, 6, 8, 9]}

↓ Post-processing

[0, 1, 2, 3], [4], [5, 6] , [7], [8, 9]

(b) Intra-topic processing.

Figure 2: Post-processing for dialogue topic segmentation.

For dialogue topic segmentation, two types of output need post-processing as shown in Figure 2. First is the inter-topic processing that lacks utterances between adjacent topics and we treat the lacking utterances as an independent topic. The second is the intra-topic processing where the utterances with a topic are discontinuous and we divide the utterances within the topic into several sub-topics by the principle of maximum continuous utterance.

For dialogue discourse parsing, the relations provided by ChatGPT are occasionally not among the candidate relations, and we randomly choose one from the candidate relations.

4. Experiments

4.1. Experimental Setup

For all experiments, we adopted the *gpt-3.5-turbo-0301* version of ChatGPT, and all hyperparameters are set to default as recommended by OpenAI. Since ChatGPT may generate empty responses (i.e., empty strings) as the result of network error or API request overloads, we resubmit the request until ChatGPT provides non-empty responses. All experiments for each task are conducted two times, and we report the mean and standard deviation values to alleviate the randomness of ChatGPT.

For dialogue topic segmentation, we adopt P_k error score (Beeferman et al., 1999) and Macro F_1 score metrics. P_k is to calculate the overlap rate between predicted and reference pieces and lower scores indicate better performance. F_1 is to measure the performance of the binary prediction. For dialogue discourse parsing, we adopt Link F_1 and Link&Rel F_1 metrics. Link F_1 metric evaluates the capability of link prediction only, and the Link&Rel F_1 metric evaluates the capability of link and relation are all correct.

Elements	Dialogue Topic Segmentation	Dialogue Discourse Parsing
Task Description	Please identify several topic boundaries for the following dialogue and each topic consists of several consecutive utterances.	According to the Segmented Discourse Rhetorical Theory, the rhetorical structure of a dialogue can be represented by a directed acyclic graph, where nodes are utterances and edges are the following 16 relations: ["Comment", "Clarification-Question","Elaboration", "Acknowledgement", "Explanation", "Conditional", "Question-Answer pairs", "Alternation","Question-Elaboration", "Result", "Background", "Narration", "Correction", "Parallel", "Contrast", "Continuation"]
Output Format	please output in the form of {'topic i':[], ... ,'topic j':[]}, where the elements in the list are the index of the consecutive utterances within the topic, and output even if there is only one topic.	please annotate the rhetorical structure of the following dialogue and represent it in the form of [index1, index2, 'relation'], where index1 and index2 are the index of two utterances, and the 'relation' is one of the above relations to connect the two utterances.
Structured Input	$0 : U_1$ $1 : U_2$ $\dots$ $n : U_n$	

Table 1: Prompt template for Dialogue Discourse Analysis.

Method	General-domain						Specific-domain	
	DialSeg711 (Daily booking service)		CNTD (Chitchat w/ background)		TIAGE (Chitchat w/o background)		ZYS (Banking expertise)	
	$P_k(\downarrow)$	$F_1(\uparrow)$	$P_k(\downarrow)$	$F_1(\uparrow)$	$P_k(\downarrow)$	$F_1(\uparrow)$	$P_k(\downarrow)$	$F_1(\uparrow)$
TextTiling	40.44	60.80	51.36	46.84	47.27	45.57	45.86	48.50
GreedySeg	50.95	40.10	53.81	53.36	52.63	49.47	44.12	50.20
TeT+CLS	40.49	61.00	43.01	50.20	**40.49**	**61.00**	43.01	50.20
UPCS	26.80	77.60	46.11	58.18	47.19	58.63	**40.99**	**52.10**
ChatGPT	**10.56(0.18)**	**89.42(0.08)**	**27.08(1.00)**	**77.36(0.35)**	42.35(2.31)	**61.31(1.87)**	56.19(0.29)	49.10(0.04)
Ratio@SOTA	253.79%	115.23%	170.27%	132.97%	95.61%	100.51%	72.95%	94.24%

Table 2: Performance comparison between ChatGPT and unsupervised baselines on dialogue topic segmentation.

Method	CNTD		TIAGE	
	$P_k(\downarrow)$	$F_1(\uparrow)$	$P_k(\downarrow)$	$F_1(\uparrow)$
BERT	-	80.80	-	66.60
T5	-	81.10	-	73.90
MGP	-	**84.70**	-	**76.20**
ChatGPT	27.08	77.36	42.35	61.31
Ratio@SOTA	-	91.33%	-	80.46%

Table 3: Performance comparison between ChatGPT and supervised baselines on dialogue topic segmentation.

4.2. Datasets

4.2.1. Dialogue Topic Segmentation

We mainly evaluate the performance of ChatGPT on three general-domain and one specific-domain dialogue topic segmentation datasets. **General-domain dataset**: **DialSeg711** (Xu et al., 2021): it is a synthetic dataset about reservations that consists of 711 English dialogues for unsupervised evaluation. Topics of the dataset are mainly about booking tickets, hotels, taxis, etc. **CNTD** (Lin et al., 2023b): it is a real-world Chinese chitchat dataset that consists of 1041, 134, and 133 conversations for training, validating, and testing, respectively. Participants always engage in a conversation around a given news report. **TIAGE** (Xie et al., 2021): it is a real-world English chitchat dataset that consists of 300, 100, and 100 dialogues for training, validating, and testing, respectively. Unlike CNTD, participants of the dataset engage in conversations aimlessly. **Specific-domain dataset**: **ZYS** (Xu et al., 2021): it is a real-world Chinese dataset about banking consultation that consists of 505 conversations for unsupervised evaluation. The conversations in this dataset are always about banking expertise.

4.2.2. Dialogue Discourse Parsing

We evaluate the performance of ChatGPT on two datasets **STAC** (Asher et al., 2016) and **Molweni** (Li et al., 2020). STAC is collected from an online game *The Settlers of Catan*, which contains 1,062 and 111 dialogues for training and testing, respectively. Molweni is based on Ubuntu Chat (Lowe et al., 2015), which contains 9,000, 500, and 500 instances for training, validating, and testing, respectively. Both datasets define 16 relation types. We follow the previous work and evaluate the performance of ChatGPT on the testing set of all datasets.

4.3. Baseline

The baselines for dialogue topic segmentation are two types: unsupervised and supervised. Unsupervised baselines: 1) **TextTiling** (Hearst, 1997): it is a traditional and common method that uses word frequencies to measure the similarity among the utterances. 2) **GreedySeg** (Xu et al., 2021): This method greedily determines segment boundaries based on the similarity of adjacent utterances com-

Methods	STAC		Molweni	
	Link F1	Link&Rel F1	Link F1	Link&Rel F1
Rule-based	60.57	20.11	67.56	25.60
DSM	71.99	53.62	76.94	53.49
SSAM	73.48	57.31	81.63	58.54
SSP	73.00	57.40	83.70	59.40
DAMT	73.64	57.42	82.50	58.91
SDDP	**74.40**	**59.60**	**83.50**	**59.90**
ChatGPT	59.91(0.13)	25.25(0.88)	63.75(0.04)	23.85(0.06)
Ratio@SOTA	80.52%	42.37%	76.35%	39.82%

Table 4: Performance comparison between ChatGPT and baselines on dialogue discourse parsing.

puted from the output of the pre-trained BERT sentence encoder. 3) **TeT+CLS** (Xu et al., 2021): TextTiling enhanced by the pre-trained BERT sentence encoder, by using output embeddings of BERT encoder to compute semantic similarity for consecutive utterance pairs. 4) **UPCS** (Xing and Carenini, 2021): it is a distant supervised method and trains an utterance-pair scoring model by sampling utterance pairs from distant corpora DailyDialog(Li et al., 2017) and Naturalconv (Wang et al., 2021b). Supervised baselines: 1) **BERT** (Lin et al., 2023a): it uses BERT (Devlin et al., 2019) to encode utterance pairs and train a binary classifier. 2) **T5** (Xie et al., 2021): it uses T5 (Raffel et al., 2020) to encode utterance pairs and train a binary classifier. 3) **MGP** (Lin et al., 2023b): it proposes a prompt-based method to fully extract topic information at several granularities from dialogues.

The baselines for dialogue discourse parsing are as follows: 1) **Rule-based**: it establishes the discourse links between adjacent utterances and treats the relation with the most common type. It can be regarded as the linear representation of discourse structure. 2) **DSM** (Shi and Huang, 2019): it alternately predicted the link and relation by incorporating historical structure; 3) **SSAM** (Wang et al., 2021a): it adopted a structure transformer and two auxiliary training signals for parsing; 4) **DAMT** (Fan et al., 2022): it combined different decoding methods for parsing; 5) **SSP** (Yu et al., 2022): it proposed a second-stage pre-trained task to enhance the speaker interaction; 6) **SDDP** (Chi and Rudnicky, 2022): it proposed to jointly optimize discourse links and relations in the dialogue and use the modified Chiu-Liu-Edmonds algorithm to generate discourse structure.

5. Experimental Results

5.1. Results on Dialogue Topic Segmentation

Table 2 shows the performance comparison between ChatGPT and unsupervised baselines on the dialogue topic segmentation task. We can find that ChatGPT performs well in the general domain, exceeding the unsupervised SOTA baseline on almost all datasets. Specifically, ChatGPT achieves the highest performance on DialSeg711, with about 254% P_k and 115% F_1 scores of SOTA baseline. We attribute this to the clear topic boundaries of DialSeg711, in which topics are usually shifted between booking tickets, hotels, taxis, etc. Besides, ChatGPT achieves 179% P_k and 133% F_1 scores of SOTA baselines on CNTD, but only achieves comparable performance compared with the SOTA baseline on TIAGE. This is because the CNTD dataset is mainly about conversations with background knowledge, making the topics usually focus on a specific argument and thus easy to identify. However, the conversations in the TIAGE dataset are always aimless and without background knowledge. This makes the topics trivial and therefore difficult to recognize. In addition, ChatGPT performs worse than most unsupervised baselines on the ZYS dataset in specific domains. This may be because, in a specific domain, recognizing topic transition requires more domain-specific knowledge as support. Therefore, it is difficult for ChatGPT to understand the topics in the specific domains.

Table 3 shows the performance comparison between ChatGPT and supervised baselines. Even under the zero-shot setting, ChatGPT still can achieve 91.33% and 80.46% F_1 scores of SOTA baseline on CNTD and TIAGE, respectively. This indicates the great potential of ChatGPT on dialogue topic segmentation.

5.2. Results on Dialogue Discourse Parsing

Table 4 shows the results of ChatGPT on dialogue discourse parsing. ChatGPT achieves 59.91 *Link* F_1 and 25.25 *Link&Rel* F_1 scores on STAC, and 63.75 *Link* F_1 and 23.85 *Link&Rel* F_1 scores on Molweni. However, the performance of ChatGPT is only comparable to the rule-based method, indicating that ChatGPT only parses rhetorical structure linearly. In addition, ChatGPT achieves about 42% and 39% performance of SOTA baseline SDDP in the Link&Rel metric on the STAC and Molweni, respectively. There is still a large room for improvement as demonstrated by the gap between ChatGPT and the supervised SOTA baselines. It showed a significant challenge ChatGPT faces in understanding hierarchical rhetorical structures.

6. Analysis

6.1. ChatGPT's Capability for Discourse Structure

ChatGPT understand the linear topic structure of general domain well Since different datasets focus on the various granularities of topics, there may be multiple reasonable topic structures for a dialogue. Therefore, solely evaluating the discrepancy between the topic structure predicted by ChatGPT and annotated by humans may underestimate the capability of ChatGPT. To further investigate the abilities of ChatGPT to understand topic structures, we randomly selected 50 dialogues from each test set and manually analyzed the ChatGPT-generated and human-annotated topic structures to determine which one is more reasonable. More details are given in Appendix A.1. The results are shown in Figure 3. On general-domain datasets, i.e., DialSeg711, CNTD, and TIAGE, ChatGPT can provide better or comparable topic structure in more than 80% of conversations compared with human-annotated. This indicates that ChatGPT can well understand general-domain topics.

In addition, ChatGPT performs differently in different scenarios of the general domains. Among the three general-domain datasets, ChatGPT performs best in the DialSeg711 dataset. This may be because the dataset is mainly about booking services, with clear topic boundaries, such as the topic shifting from booking a hotel to booking a flight. Moreover, although CNTD and TIAGE are both chitchat datasets, ChatGPT performs better on CNTD than on TIAGE. This may be because participants in CNTD tend to have conversations around a given reports, leading to the more focused topics and clear topic boundaries. While participants in TIAGE engage in rambling small talk, leading to more trivial and less sustainable topics.

However, ChatGPT performs poorly in recognizing specific domain topics. On the ZYS dataset, 50% of the topic structures provided by ChatGPT are inferior to the human-annotated structures. This may be due to ChatGPT having a wealth of general-domain knowledge, but a lack of specialized domain knowledge, such as banking expertise.

ChatGPT hardly understands the hierarchical rhetorical structure To further study the abilities of ChatGPT to understand the hierarchical rhetorical structure, we explore the performance on various links with different distances as shown in Figure 4. We can observe that the Rule-based method has 100% link accuracy at the distance 1 on both datasets due to all the links being established in the adjacent utterances. SDDP can recognize the links and relations at various distances and have a downward trend with the distance increasing, which indicates that long-distance links are more difficult to recognize. However, ChatGPT can only recognize the links at a distance of 1 and hardly recognize the links at a distance greater than 1, which has a similar trend with the Rule-based method that parses the hierarchical rhetorical structure linearly. It further suggests that ChatGPT only understands

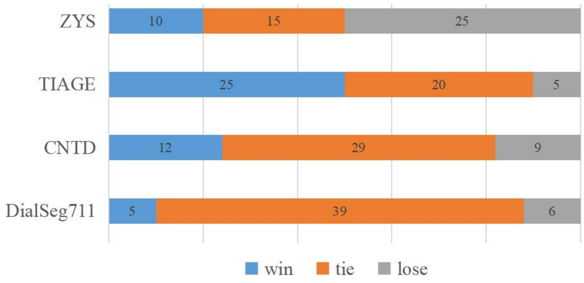


Figure 3: Manual pair-wise evaluation between ChatGPT-generated and human-annotated topic structures. **win** indicates that ChatGPT-generated topic structure is more reasonable, **tie** indicates that ChatGPT-generated and human-annotated topic structures are equally reasonable, and **lose** indicates that human-annotated topic structure is more reasonable.

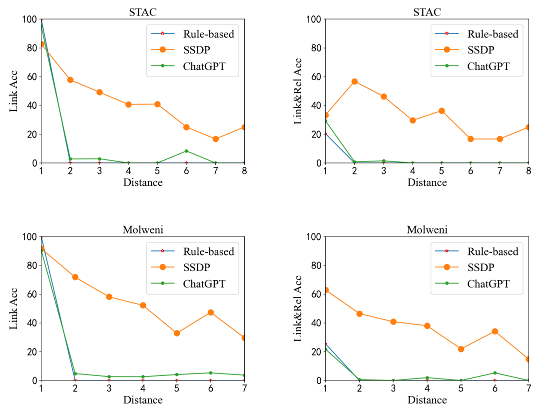


Figure 4: The comparison of performance between ChatGPT and baselines on STAC and Molweni at various distances. If there is a link between U_j and U_i, the distance of the link is defined as $i - j$.

the hierarchical rhetorical structure linearly.

Furthermore, we investigate the performance of ChatGPT in identifying relation types, as shown in Table 5. We can observed that ChatGPT mainly recognizes most of the high resource relation types, such as Clarification_question, Question-answer pair, Acknowledgment, and Continuation. This suggests that ChatGPT, as a general conversation model, is capable to some extent of understanding the types of relation that are common in the conversations. In addition, even though Comment is also a high resource relation type, it is difficult for ChatGPT to recognize. This may be because Comment is a type of relation with subjective opinions, while ChatGPT is strictly restricted to output subjective opinions due to its security, which makes it difficult to identify. Finally, for some low resource relation types, such as Correction, Contrast, etc., ChatGPT is usually difficult to identify. This suggests that ChatGPT still faces great challenges in identifying

(a)

Vallina
Task Description
Output Format

Dialogue:
0. how are you doing today
1. hello , i am doing very well.
...
14. i like red and pink and blue
15. those are pretty colors as well .
Annotation:
{'Topic 0': [0, 1, 2, 3, 4],
'Topic 1': [5, 6, 7, 8, 9, 10],
'Topic 2': [11, 12, 13, 14, 15]}

Structured Input

CoT
Task Description
Output Format

Dialogue:
0. how are you doing today
1. hello , i am doing very well.
...
14. i like red and pink and blue
15. those are pretty colors as well .

Let's think step by step.

Utterances 0-4 are about introducing themselves and talking about their upcoming wedding plans.
...
Utterances 11-15 focused on discussing personal preferences.

Structured Input

(a)

Vallina
Task Description
Output Format

Dialogue:
0: skinnylinny said, Who is yiin?
...
4: sabercat said, but he should go away for good!
Annotation:
[0, 1, 'Question-answer pair']
...
[3, 4, 'Contrast']

Structured Input

CoT
Task Description
Output Format

Dialogue:
0: skinnylinny said, Who is yiin?
...
4: sabercat said, but he should go away for good!

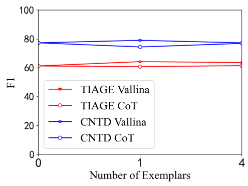
Let think step by step

step 1: skinnylinny asked a question and asked who is yiin, so there is no edge since this is the starting point.
step 2: IG answered skinnylinny's question, and he doesn't know, so the edge is "[0, 1, 'Question-answer pair']"
...
step 5: sabercat contrasted the content with what he said before, so the edge is "[3, 4, 'Contrast']"

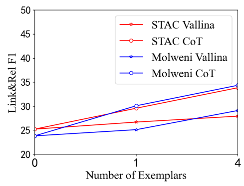
Structured Input

(b)

Figure 5: (a) and (b) show the details of in-context learning with one exemplar for dialogue topic segmentation and dialogue discourse parsing, respectively.



(a)



(b)

Figure 6: (a) and (b) show the ICL performance of ChatGPT on dialogue topic segmentation and dialogue discourse parsing, respectively.

relation in low resource scenarios.

6.2. Impact of In Context Learning on ChatGPT

In this section, we investigated the impact of in-context learning (Min et al., 2022) on ChatGPT's understanding of discourse structure. We select at most 4 exemplars randomly from the training set of the supervised dataset due to the token limitation of ChatGPT. Then, we introduce the exemplars into the prompt in two types as shown in Figure 5: Vanilla and Chain-of-Thought (CoT)(Wei et al., 2022). The vanilla type directly inserts the dialogue and its discourse structure between the output format and structured input in the prompt. The CoT type not only provides the dialogue and its discourse structure but also some intermediate steps are written manually for deriving discourse structure. We conduct the experiments two times and report the average performance.

Figure 6 shows that neither Vanilla nor CoT few-shot can improve the performance of ChatGPT on dialogue topic segmentation with the number of exemplars increasing. This shows that ChatGPT has a good understanding of linear topic structures and more exemplars can not enhance the capabilities of ChatGPT on topic structure significantly.

However, both vanilla and CoT types can improve the performance of ChatGPT on dialogue discourse parsing as the number of exemplars increases. This demonstrates the insufficiency of ChatGPT to understand hierarchical rhetorical structures and more exemplars can significantly alleviate the deficiencies of ChatGPT. It is worth noting that the CoT type helps ChatGPT more since it provides intermediate steps for deriving discourse structures. This suggests that dialogue discourse parsing is a complex task that requires multi-step reasoning.

6.3. Ablation Study of Prompt Components

To study the impact of the three components (task description, output format, and structured input) that make up the prompt on the performance of two tasks, we conducted an ablation study as shown in Table 6. More details about the variants of different components are given in Appendix A.2.

We first investigated the impact of different sources of task descriptions (manually written and ChatGPT generated) on performance. Specifically, we used the original manually written task descriptions as a reference to ask ChatGPT to generate corresponding task descriptions. The results shown in the third row of Table 6 indicate that the performance difference between the task descriptions generated by ChatGPT and those written manually is not significant, suggesting that the performance of ChatGPT is not sensitive to changes in task descriptions.

Then, we delved into the impact of different output forms (ours and traditional) on performance. Specifically, for dialogue topic segmentation, we instruct ChatGPT to output a 0/1 sequence for the utterance list, where '1' indicates the current utterance is the end of a topic, as shown in Figure 1. For dialogue discourse parsing, we replace the sparse matrix we adopted with an adjacency matrix. The results in the fourth row of Table 6 showed a significant performance degradation on both tasks. We found it is because ChatGPT may be insensitive to the number of utterances in a dialogue by our error analysis. For example, for a dialogue with N utterances, ChatGPT cannot always output a 0/1 list of length N to represent the topic structure, or an adjacency matrix of shape $N \times N$ to represent

Type	Molweni		STAC	
	Number(Prop(%))	Accuracy(%)	Number(Prop(%))	Accuracy(%)
Comment	1081(27.04)	1.2	165(14.65)	7.27
Clarification_question	952(24.34)	18.49	33(2.93)	-
Question-answer pair	808(20.66)	28.84	305(27.09)	27.21
Continuation	275(7.03)	10.91	113(10.04)	19.47
Acknowledgment	131(3.35)	11.45	147(13.06)	18.37
Explanation	119(3.04)	1.68	31(2.75)	16.13
Elaboration	59(1.51)	15.25	101(8.97)	23.76
Correction	53(1.36)	1.89	21(1.87)	-
Contrast	37(0.95)	2.70	44(3.81)	13.64

Table 5: Performance of ChatGPT for relation recognition in dialogue discourse parsing task. Prop refers to the proportion of the relation instances.

Prompt	DTS				DDP	
	DialSeg711	CNTD	TIAGE	ZYS	STAC	Molweni
Ours	89.42	77.36	61.31	49.60	25.25	23.85
ChatGPT-generated task description	88.28	76.43	61.45	48.44	23.82	23.26
Sequence labeling/Adjacency matrix output	51.95	59.05	53.27	40.67	12.53	13.37
Unstructured input	83.21	74.01	58.69	44.62	21.54	21.22

Table 6: Ablation study of different components of prompt. F_1 and *Link&Rel* F_1 performance are reported for Dialogue Topic Segmentation (DTS) and Dialogue Discourse Parsing (DDP), respectively.

Task	Dataset	#Dial.	Avg.#NM.	Ratio.(%)
DTS	TIAGE	100	0.8	0.80
	CNTD	133	3.2	2.40
	DialSeg711	711	68	9.56
	ZYS	505	24	4.75
DDP	STAC	111	2	1.80
	Molweni	500	3.6	0.72

Table 7: The ratio that ChatGPT does not follow the output format on each dataset. “#Dial.” is the number of dialogue for testing. “Avg. #NM.” indicates the average number of dialogues that ChatGPT does not follow the output format under two-times experiments. “Ratio (%)” denotes the percentage of “Avg. #NM.” and “#Dial.”.

the discourse structure, with a percentage of 52% and 65%, respectively, which introduces serious evaluation errors.

Finally, we explored the impact of structured or unstructured inputs on performance. The last row of Table 6 showed there is only slight performance degradation after removing the structured number. Error analysis reveals that ChatGPT ignores some of the utterances without the help of the number indication, which requires more post-processing operations for evaluation, resulting in performance degradation.

6.4. Robustness of ChatGPT

Because ChatGPT can not always output in the specified format, we investigate the instruction-following capabilities of ChatGPT. For each dataset, we report the ratio that ChatGPT does not follow the output format as shown in Table 7. We can see that ChatGPT can not fully follow the instructions on each dataset, reaching a maximum of 9.56% on the DialSeg711. We analyzed the samples on DialSeg711 that do not follow instructions and found that more than 90% required inter-topic processing, as shown in Figure 2. We attribute this to the fact that ChatGPT may ignore topics containing fewer utterances during the generation even if it has recognized the topics. This indicates that ChatGPT's robustness is still an issue for task completion.

6.5. Case Study

To further demonstrate ChatGPT's success in understanding linear topic structure and failure in hierarchical rhetorical structure, we conducted case studies as shown in Table 8 and Table 9. From the case in Table 8, we can see that human annotation only divided the dialogue into two topics (U_1-U_4 and U_5-U_{16}). However, there are more topics among U_5 to U_{16}, including hunting, fishing, and enjoying life. ChatGPT successfully identifies these topics, giving reasonable topic boundaries. This indicates that ChatGPT can understand the linear topic structure well in the general domain.

Table 9 shows a case from the STAC dataset. Human annotation annotates several discourse relations between utterances with longer distances, such as *(1, 4): Question-Elaboration*, *(2, 6): Elaboration*, etc. However, ChatGPT always establishes

Number	Utterance	Annotation	ChatGPT
0	how are you ? being an old man , i am slowing down these days	0	0
1	hi , my dad is old as well , they live close to me and i see them often	0	0
2	that is a great thing honor your dad with your presence	0	0
3	sure , i pick him up for church every sunday with my ford pickup	1	1
4	sounds wonderful my wheelchair can go very fast on various terrains	0	0
5	i guess that means you do not go hunting often ? i love hunting , i own 3 guns	0	0
6	hunting ? i served in the marines , yes i hunt	0	0
7	yeah me too , i am conservative so i love church and hunting	0	1
8	what do you like to hunt ? do you ever fish ?	0	0
9	fishing is good . i love fishing as well	0	0
10	fishing is a better choice sometimes for my one leg	0	0
11	yes that must be hard , i hope things get better for you	0	0
12	i enjoy life , it is what it is these days .	0	0
13	yes i agree . i try to enjoy life too , whenever i am not working	0	1
14	well , you better enjoying working so you can enjoy more of your time .	0	0
15	yeah but i go to church every sunday so my weekends are usually booked	0	0

Table 8: Case study for dialogue topic segmentation and the cases are from the TIAGE dataset. '1' indicates the end of a topic.

Number	Speaker	Utterance	Annotation	ChatGPT
0	somdechn	I need wood, clay or ore,I can give Sheep	(0,1): Question-answer_pair	(0,1): Elaboration
1	Shawnus	i can trade wood	(0,2): Question-answer_pair	(1,2): Comment
2	ztime	just spent it all	(2,3): Comment	(2,3): Comment
3	ztime	sorry	(1,4): Question-Elaboration	(3,4): Continuation
4	somdechn	1 sheep for 1 wood?	(4,5): Question-answer_pair	(4,5): Question-answer_pair
5	Shawnus	2 sheep 1 wood	(2,6): Elaboration	(5,6): Comment
6	ztime	sorry empty	(6,7): Explanation	(6,7): Continuation
7	ztime	tough times..	(5,8): Comment	(7,8): Comment
8	Shawnus	hopefully i dont roll a 7	(8,9): Continuation	(8,9): Continuation
9	Shawnus	and that biotes me in the arse	(9,10): Correction	(9,10): Correction
10	Shawnus	bites*		

Table 9: Case study for dialogue discourse parsing and the case are from STAC dataset.

the discourse relation between adjacent utterances linearly, showing it hardly understands the hierarchical rhetorical structure.

7. Conclusion

In this paper, we conducted a systematic inspection of ChatGPT's capabilities in two dialogue discourse tasks (topic segmentation and discourse parsing) for its deep semantic understanding of linear and hierarchical discourse structures. We first crafted the prompt template with the task description, output format, and structured input to guide ChatGPT to complete the task. Then, we conducted the experiments on four popular topic segmentation datasets and two discourse parsing datasets. The experimental results reveal that ChatGPT has a good understanding of topic structure in general-domain conversations but struggles in specific-domain conversations. Besides, ChatGPT hardly understands the rhetorical structure, which is more complex and needs to consider long-distant dependent relations of utterances. In-depth analysis indicates that ChatGPT could give finer-granularity topic structures than human annotations but only parses the hierarchical rhetorical structures linearly. Besides, we delved into the impact of in-context learning on ChatGPT and observed that chain of thought can significantly improve the capabilities of ChatGPT to parse the hierarchical structures. In addition, we delved into the impact of various prompt components and observed that output format contributes the most. Finally, the robustness of ChatGPT is still an issue of concern. We hope these findings provide a foundation for dialogue discourse analysis in future research.

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A. Appendix

A.1. Details of Human Evaluation for Topic Structures

To compare the topic structures annotated by humans and ChatGPT, we recruited 3 annotators whose native language is Chinese. All of the annotators are undergraduate students studying at a university where English is the official language. Each annotator is instructed to compare the topic structures annotated by ChatGPT and humans in order to determine which one is more reasonable. The model names remain anonymous, and the positions of the model outputs are randomly swapped. We finally adopted voting to avoid individual bias.

A.2. Details of the Variants of Various Components in Prompt

The components of the prompt we designed mainly consist of task description, output format, and structured input. We introduce the variants of each component in detail below.

Task Description The task description mainly includes two types: human-written and ChatGPT - generated, which guides ChatGPT to complete the task as required. The descriptions written by humans are shown in Table 1. For each task, we

Prompt
The following is a description to guide the generative model to complete the dialogue topic segmentation task/dialogue discourse parsing task.
<Task description written by humans>
Please generate a similar description with several sentences.

Table 10: Prompt that the task description be generated using ChatGPT.

describe the goal of the task, such as identifying several boundaries for dialogue topic segmentation, to instruct ChatGPT to understand and complete the task. In addition, to get the task description generated by ChatGPT, we feed the task description written by humans to ChatGPT and instruct ChatGPT generate a similar description, and the prompt is shown in Table 10.

Output Format Output format for dialogue topic segmentation mainly includes two forms: python dictionary and sequence labeling. For example, given a dialogue consisting of 10 utterances, denoted as $\{u_1, u_2, u_3, \cdots, u_{10}\}$, where u_1-u_4, u_5-u_8 and u_9-u_{10} are considered different topics. Python dictionary form is as 'topic 1': [1, 2, 3, 4], 'topic 2': [5, 6, 7, 8], 'topic 3': [9, 10], where the elements in the list are the index of the consecutive utterances within the topic. Sequence labeling form is a list of length 10 containing 0 or 1, where 1 indicates the end of the topic, as follows $[0, 0, 1, 0, 0, 1, 0, 1]$.

Output format for dialogue discourse parsing mainly includes sparse matrix and adjacency matrix forms. For example, given a dialogue consisting of 3 utterances, denoted as $\{u_1, u_2, u_3\}$, where u_2 and u_1 form the Question-answer pair type, and u_3 and u_1 form the Clarification_question type. The sparse matrix form is as [[1, 2 Question-answer pair], [1, 3, Clarification_question]], where the elements in the list are the indexes of two utterances, and the relation type. The adjacency matrix form is an adjacency matrix of shape 3×3, as follows [[0, 0, 0], [Question-answer_pair, 0, 0], [Clarification_question, 0, 0]], where the element w_{ij} in the adjacency matrix is the relation type between u_i and u_j.

Input Format Input format include structured and unstructured types, referring to whether or not feed the utterances utterance to ChatGPT line by line. For example, given a dialogue consisting of 3 utterances, denoted as $\{u_1, u_2, u_3\}$. The structured form is as "1: u_1 \n 2: u_2 \n 3: u_3: \n", while unstructured form means removing these utterance indicators.