

Multi-tasking Dialogue Comprehension with Discourse Parsing

Yuchen He^{1,2,3,#}, Zhuosheng Zhang^{1,2,3,#}, Hai Zhao^{1,2,3,*}

¹ Department of Computer Science and Engineering, Shanghai Jiao Tong University

² Key Laboratory of Shanghai Education Commission for Intelligent Interaction and Cognitive Engineering, Shanghai Jiao Tong University

³ MoE Key Lab of Artificial Intelligence, AI Institute, Shanghai Jiao Tong University
{21644h, zhangzs}@sjtu.edu.cn, zhaohai@cs.sjtu.edu.cn

Abstract

Multi-party dialogue machine reading comprehension (MRC) raises an even more challenging understanding goal on dialogue with more than two involved speakers, compared with the traditional plain passage style MRC. To accurately perform the question-answering (QA) task according to such multi-party dialogue, models have to handle fundamentally different discourse relationships from common non-dialogue plain text, where discourse relations are supposed to connect two far apart utterances in a linguistics-motivated way. To further explore the role of such unusual discourse structure on the correlated QA task in terms of MRC, we propose the first multi-task model for jointly performing QA and discourse parsing (DP) on the multi-party dialogue MRC task. Our proposed model is evaluated on the latest benchmark Molweni, whose results indicate that training with complementary tasks indeed benefits not only QA task, but also DP task itself. We further find that the joint model is distinctly stronger when handling longer dialogues which again verifies the necessity of DP in the related MRC.

1 Introduction

Machine reading comprehension (MRC) is essentially formed as a question-answering (QA) task subject to a given context like passages (Hermann et al., 2015; Rajpurkar et al., 2016). Recently, more and

more attention is raised on a special MRC type whose given context is a dialogue text (Reddy et al., 2019; Choi et al., 2018). Training machines to understand dialogue has been shown more challenging than the common MRC as every utterance in dialogue has an additional property of speaker role, which breaks the continuity as that in common non-dialogue texts due to the presence of crossing dependencies which are commonplace in multi-party chat (Allen et al., 1994; Perez and Liu, 2017). Thus dialogue demonstrates quite a different discourse relationship mode from the non-dialogue in that consecutive utterances usually have a type of discourse relation (Afantenos et al., 2015; Shi and Huang, 2019; Li et al., 2020; Li et al., 2021). Recently, there emerges an even more challenging dialogue MRC task, the multi-party one, which involves more than two speakers in the given dialogue passage (Li et al., 2020; Li et al., 2021) and further demonstrates unusual discourse structures such as quite a lot of adjacent utterances do not have any semantic relationship. Being harder for comprehension, multi-party dialogue MRC has a great value of application which can be applied to frontiers such as intelligent human-computer interface and knowledge graph building.

As shown in Figure 1, our work tries to extract the answer to the given question from the multi-party dialogue. Unlike texts used in typical MRC tasks, the multi-party dialogue has manifold sentence patterns and the topics of adjacent sentences can be totally irrelevant sometimes. The context of multi-party dialogues is defined by abstract discourse structures rather than sentence positions.

Considering that the question-answering (QA) and

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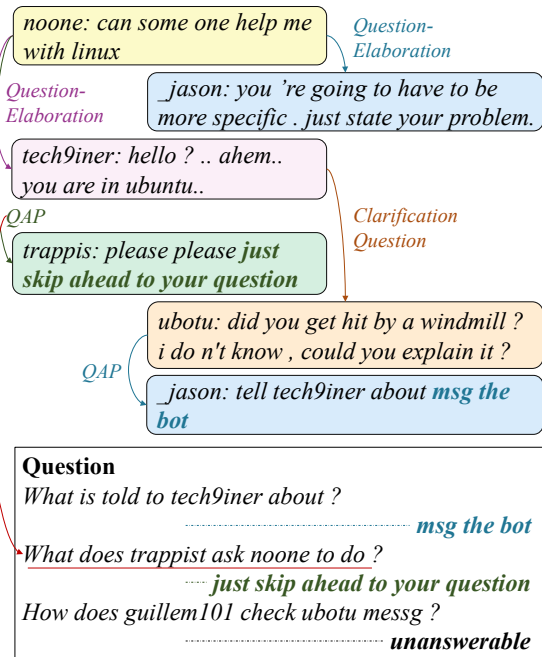


Figure 1: An example of multi-party dialogue MRC in the Molweni dataset (Li et al., 2020).

discourse parsing (DP) tasks in the multi-party dialogue MRC are correlated and share close relations, it is supposed to naturally model these two tasks as one. Intuitively, the discourse structure entailed in the DP task would be helpful for modeling the inner utterance relationships in the dialogue context. For example, as Figure 1 shows, the first and fourth utterances is a question-answering pair (QAP) (which is marked by the red arrow) which helps strengthen the connection between the two utterances and might help answer the second question. Meanwhile, the QA task aims to extract the salient span-level answers that potentially benefit DP. However, it is surprising such a model design does not appear until this work makes the first attempt by doing so.

In this work, we present a unified model for the multi-party dialogue MRC, which for the first time formally integrates such two diverse tasks for one purpose in multi-task learning (MTL) mode. We expect the model can deal with both QA and DP subtasks well and perform better than in individual tasks. By carefully selecting a proper testbed, our proposed method will be evaluated on the latest multi-party dialogue MRC benchmark, Molweni (Li et al., 2020), which both tasks can exploit accurate human

annotations, to guarantee the reliability of our results. Experimental results indicate that multi-tasking the complementary tasks indeed benefits not only QA task, but also DP task itself. We further find that the joint model performs better when handling longer dialogues, which proves the strong correlations between the two tasks. As a result, our model also achieves state-of-the-art results on the Molweni multi-party dialogue dataset.

2 Background and Related Work

2.1 QA-based MRC

MRC task aims at teaching the machine to answer questions according to given reference texts (Hermann et al., 2015; Rajpurkar et al., 2016; Zhang et al., 2020b). The study of MRC has experienced two significant peaks, namely, 1) the burst of deep neural networks (Yu et al., 2018a; Seo et al., 2017); 2) the evolution of pre-trained language models (PrLMs) (Devlin et al., 2019; Clark et al., 2020). In the early stage, MRC was regarded as the form of triple-style (passage, question, answer) question answering (QA) task, such as the cloze-style (Hermann et al., 2015; Hill et al., 2016), multiple-choice (Lai et al., 2017; Sun et al., 2019), and span-QA (Rajpurkar et al., 2016; Rajpurkar et al., 2018). Among these types, span-based QA MRC has aroused the most research interests.

Recently, more and more attention is raised on a special MRC type whose given passage is a dialogue text (Reddy et al., 2019; Choi et al., 2018). In this work, we deal with the QA-based MRC task on multi-party dialogues, which requires the machine to extract a consecutive piece from the original dialogue. Multi-party dialogue comprehension involves more than two speakers, and there is a complicated phenomenon of crossing dependencies in multi-party dialogues. It has been shown much more challenging than the traditional MRC models (Li et al., 2020) due to the requirement to handle quite different discourse relationship modes from common non-dialogue plain text, where discourse relations may quite possibly connect two far apart utterances.

2.2 Discourse Parsing

Discourse parsing focuses on the discourse structure and relationships of texts, whose aim is to predict the

relations between discourse units so as to disclose the discourse structure between those units. Discourse parsing has been studied by researchers especially in linguistics for decades. Previous studies have shown that discourse structures are beneficial for various natural language processing (NLP) tasks, including dialogue understanding (Asher et al., 2016; Takanobu et al., 2018; Gao et al., 2020; Jia et al., 2020), question answering (Chai and Jin, 2004; Verberne et al., 2007; Mihaylov and Frank, 2019), and sentiment analysis (Cambria et al., 2013; Nejat et al., 2017).

Most of the previous works for discourse parsing (DP) are based on the linguistic discourse datasets, such as Penn Discourse TreeBank (PDTB) (Mitsakaki et al., 2004) and Rhetorical Structure Theory Discourse TreeBank (RST-DT) (Mann and Thompson, 1988). PDTB focuses on shallow discourse relations but ignores the overall discourse structure (Qin et al., 2017; Cai and Zhao, 2017; Bai and Zhao, 2018; Yang and Li, 2018). In contrast, RST is constituency-based, where related adjacent discourse units are merged to form larger units recursively (Braud et al., 2017; Wang et al., 2017; Yu et al., 2018b; Joty et al., 2015; Li et al., 2016; Liu and Lapata, 2017). Compared with the traditional DP tasks which are linguistically motivated, our work is application-driven from dialogue comprehension scenarios and devotes itself to handling the multiparty dialogues that involve more complex utterance relationships and speaker role transitions. However, most of the previous constituency-based DP tasks only focus on plain texts and does not allow non-adjacent relations, which makes it inapplicable for modeling multi-party dialogues. In terms of serving such a purpose, we are the first to present a pre-trained language model (e.g., BERT (Devlin et al., 2019)) based method for discourse parsing to our best knowledge.

3 Methods

3.1 Feature Extraction

Figure 2 overviews our multi-party dialogue MRC model which parallelly includes modules of QA and DP. We apply PrLMs to encode our dialogue context and questions. Before data input, we first append padding symbols to fill the content for texts with tokens less than the preset value and add separators ([CLS] and [SEP]) between question and dialogue

or adjacent utterances, following the standard process of using PrLMs (Devlin et al., 2019). The positions of separators in the dialogue will be recorded to separate single utterance information for further DP task. We put the question in front of the dialogue to take full advantage of the knowledge learned in the next sentence prediction task of the pre-training stage and get abundant semantic information of the question. We concatenate the question $Q = w_q^1 w_q^2 \dots w_q^n$ and dialogue context $D = w_d^1 w_d^2 \dots w_d^m$ as a whole to feed the PrLM encoder and get the output text feature: $S = \text{encode}([CLS], Q, [SEP], D, [SEP])$, where S is the contextualized sequence representations, and w_q^i ($1 \leq i \leq n$) and w_d^j ($1 \leq j \leq m$) represent tokens of texts. Variables n and m respectively mean the number of tokens in the question and dialogue.

The output feature can be used in QA task directly, but for DP task, we have to do further processing to get the eigenvectors that represent the utterance relationship. After obtaining the features, we fetch the vectors at corresponding positions of separators to represent the utterances respectively. On the grounds of Euclidean and cosine distance and considering the asymmetry of utterance relationship, we use this cascade as the relationship feature to do DP task as Figure 2 shows: $F_{i,j} = (E_{SEP}^i, E_{SEP}^j, E_{SEP}^i - E_{SEP}^j, E_{SEP}^i \cdot E_{SEP}^j)$, where E_{SEP}^i is the output feature of the i^{th} separator in the dialogue for the i^{th} utterance.

3.2 Prediction

For the QA task, we treat question answering as a multi-classification task by using fully connected layers to predict the start logits and end logits of the answer over the given dialogue. Then the most likely start and end positions are computed by using softmax as an activated function and the answer piece is extracted from the initial dialogue. Take the prediction of the start position for example: $P_s = \text{argmax}(\text{softmax}(W_s S))$, where P_s is the predicted start position, W_s is the weight matrix and S is the text feature. It is important to note that in this work, we need to deal with unanswerable questions. A score of the most likely answer span will be calculated and compared to a no-answer score to determine whether the question is answerable (Zhang et al., 2020a).

For the DP task, we represent the relationships of

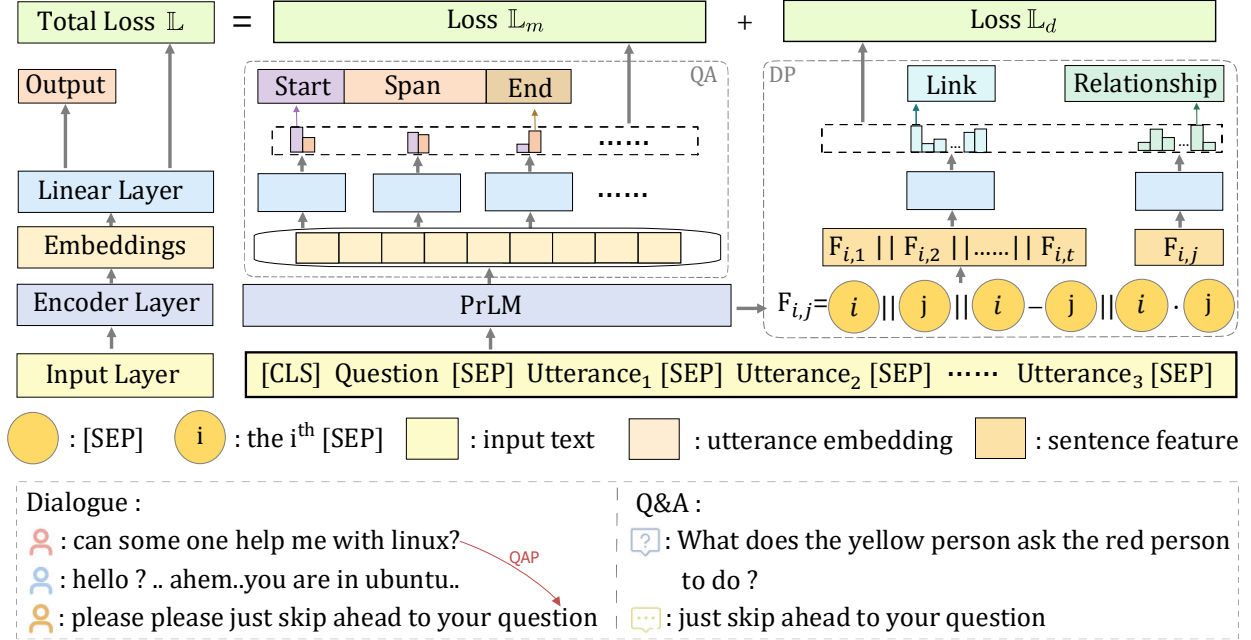


Figure 2: The overview of the joint model. The top half part is the PrLM. The left lower part is the QA model, and the right lower part is the DP model.

utterances by dependency trees as Figure 4 shows, and if there exists some utterances not depending on any others, then we assign it to depend on the root. The prediction is divided into two parts. The first one is link prediction: we calculate the existence of relationship between utterances, that is to say, for the i^{th} utterance, we adopt a matrix decomposition by performing SVD over $(F_{i,1}, F_{i,2}, \dots, F_{i,t})$ for significant eigenvector to indicate which utterance it depends on, where t is the max number of utterances in a dialogue. Meanwhile we also use $F_{i,j}$ to predict the kind of the relationship between the i^{th} and j^{th} utterance which is the second part called relationship prediction. We regard these two parts as multi-classification and input the logits into softmax layer and argmax layer to get final answer:

$$\begin{aligned} L_i &= \operatorname{argmax}(\operatorname{softmax}(\mathbf{W}_l[F_{i,1}, F_{i,2}, \dots, F_{i,t}])), \\ R_{i,j} &= \operatorname{argmax}(\operatorname{softmax}(\mathbf{W}_r F_{i,j})), \end{aligned} \quad (1)$$

where L_i is the predicted utterance number which the i^{th} depends on, $R_{i,j}$ is the predicted relationship between the i^{th} and j^{th} utterances, \mathbf{W}_l and \mathbf{W}_r are the weight matrix.

3.3 Loss Function

Our objective in QA task is to predict the start and end positions for the answers. Assume that there are K tokens in total in the input embedding, then we regard it as multi-classification task with K different labels where one label equals to one position. We firstly use softmax as activated function to normalize the logits, then use cross entropy as loss function to calculate the loss of start and end prediction respectively, and finally average them as total loss of QA task.

$$\mathbb{L}_m = -\frac{1}{2N} \sum_{n=0}^{N-1} \sum_{k=0}^{K-1} (y_s^{n,k} \log p_s^{n,k} + y_e^{n,k} \log p_e^{n,k}). \quad (2)$$

where \mathbb{L}_m is the loss of QA task, N is the batch size, K is the number of labels, $y_s^{n,k}$ equals to one if the answer of the n^{th} sample exactly starts at the k^{th} token or otherwise it equals zero, $p_s^{n,k}$ is the probability of the start position of the n^{th} being predicted to be the k^{th} token and $y_e^{n,k}$ and $p_e^{n,k}$ are similar to $y_s^{n,k}$ and $p_s^{n,k}$ for end position prediction.

For the DP task, the number of relationships is 16 in Molwani as Table 1¹ shows, and the max num-

¹Detailed information can be seen in Li et al. (2020)

	Speaker	Utterance
U ₀	sipher	bacon5o there 's no "fixmbr" with ubuntu .
U ₁	Bacon5o	i dont want ubuntu , it does n't support my internet , thus i can not use it
U ₂	morfic	my ati has no aiglx support so i ca n't speak for how FILEPATH is
U ₃	morfic	your internet is different from mine ? damn bush and his internets !
U ₄	Bacon5o	my internet is different why you ask ?
U ₅	morfic	your possessive " my " on the internet
U ₆	Bacon5o	i use a wireless accesspoint that plugs into my usb

(a) Dialogue example from Ubuntu Chat Corpus

Question	Answer
Why does Bacon5o not want ubuntu ?	it does n't support my internet
What does Bacon5o use to plugs into usb ?	a wireless accesspoint
What did sipher use ?	(unanswerable question)

(b) Q&A example for multi-party dialogue MRC

Figure 3: (a) is an example of dialogue in Molweni. (b) shows questions and corresponding answers based on the dialogue in (a). It is noteworthy that unanswerable questions exist.

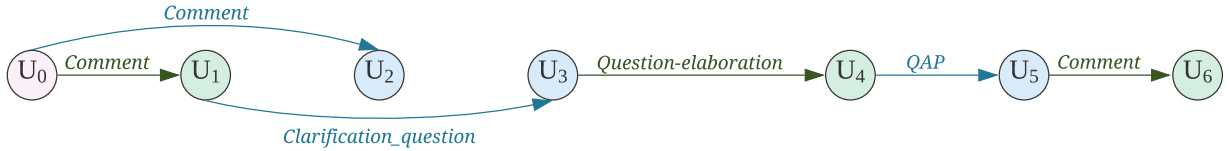


Figure 4: A dependency tree example for DP task based on the dialogue in Figure 3.

ber of utterances in one dialogue is T . Then we regard link prediction and relationship prediction as multi-classification with $T + 1$ labels and 16 labels respectively, where the additional one label in link prediction is the root. Using cross entropy, the loss function of link prediction \mathbb{L}_l is:

$$\mathbb{L}_l = -\frac{1}{N} \sum_{n=0}^{N-1} \frac{1}{T} \left(\sum_{t_1=0}^{T-1} \sum_{t_2=0}^T y_l^{t_1, t_2} \log p_l^{t_1, t_2} \right), \quad (3)$$

where $y_l^{t_1, t_2}$ equals to one if the t_1^{th} utterance depends on the t_2^{th} one or otherwise it is zero, and $p_l^{t_1, t_2}$ is the probability of the t_1^{th} utterance being predicted to be dependent on the t_2^{th} one. The loss function of relationship prediction \mathbb{L}_r is:

$$\mathbb{L}_r = -\frac{1}{N} \sum_{n=0}^{N-1} \frac{1}{T} \left(\sum_{t=0}^{T-1} \sum_{i=0}^{15} y_r^{t, i} \log p_r^{t, i} \right), \quad (4)$$

where $y_r^{t, i}$ equals to one if the t^{th} utterance depends any other utterance and the relationship is the i^{th} kind or otherwise it is zero, and $p_r^{t, i}$ is the probability of the t^{th} utterance being predicted to be dependent on

one utterance and the relationship is the i^{th} one. The loss of DP task \mathbb{L}_d is the sum of \mathbb{L}_l and \mathbb{L}_r . Then we add up \mathbb{L}_d with the loss of QA task in Eq.(2) as total loss \mathbb{L} for the joint model.

4 Experiments

4.1 Molweni Dataset

Molweni dataset (Li et al., 2020) is multi-party dialogue comprehension dataset derived from Ubuntu Chat Corpus (Li et al., 2020). It has 9, 754 dialogues, 86, 042 utterances and 30, 066 QAPs in total. Among the QAPs, the unanswerable questions account for 14.26%. Types of questions are mainly 5W1H which means questions start with *What, Where, When, Who, Why*¹. For DP task, Molweni has discourse structures for each dialogue and there are 78, 245 discourse relations between utterances in total, among which there are 16 different kinds as Table 1 shows.

Molweni uses both manual check and programmatic check to guarantee its reliability. The Fleiss kappa is 0.91 for link annotation and 0.56 for link&relation annotation which indicates that Mol-

	Relation Type	Ratio (%)		Relation Type	Ratio (%)
1	Comment	31.7	9	Explanation	1.6
2	Clarification question	24.0	10	Correction	1.2
3	QAP	20.1	11	Contrast	1.2
4	Continuation	6.7	12	Conditional	1.0
5	Acknowledgment	3.2	13	Background	0.4
6	Question-elaboration	3.0	14	Narration	0.3
7	Result	2.6	15	Alternation	0.2
8	Elaboration	2.2	16	Parallel	0.2

Table 1: The kinds of discourse relations

weni has high reliability and consistency.

4.2 Metrics

Following Li et al. (2020), we use F1 score and exact match (EM) as metrics in QA task. For DP task, we use micro F1 score to judge the link prediction and relationship prediction respectively. For relationship prediction, only when the link and relationship are both correct, it will be counted as positive.

4.3 Detailed Settings

We use three different settings of BERT (Devlin et al., 2019) as the PrLM: BERT-base-uncased (BERT_{base}), BERT-large-uncased (BERT_{large}) and BERT-large-uncased-whole-word-masking (BERT_{wwm}). The hidden size of each model is 768, 1024, and 1024 respectively. The max sequence length is 512 in tokens, and the max utterance number per dialogue is 14 according to Li et al. (2020). Based on the results on the dev set, we set the learning rate to $5e^{-5}$ for BERT_{base}, $3e^{-5}$ for BERT_{large}, $3e^{-5}$ for BERT_{wwm}, and set the dropout rate of DP task to 0.4 for BERT_{base}, 0.4 for BERT_{large}, 0.1 for BERT_{wwm}.

In the fine-tuning stage, we train all the models for 2 epochs. We try three different values 0.5, 1, and 2 as the ratio of \mathbb{L}_m to \mathbb{L}_d . We finally set the ratio to 1 which gets the best result.

4.4 Results

The results of our experiments together with public results and human performance are in Table 2. We see that compared to QA-only model, the results of QA in multi-tasking model make a progress, and

this may also apply to the results of DP task. It shows that our joint model indeed leads to a mutual promotion. Furthermore, we compare our results with the benchmark of Li et al. (2020) in Table 2, showing that our model achieves new state-of-the-art in both QA and DP task.

Besides, by analysing the performances of our joint model under different parameters, we discover that the results of the two tasks are closely linked to each other. For example, when the DP task in our model is overfitting or even not convergent at all, the performance of QA task will also decrease to a certain extent which verifies the close correlations between QA and DP.

Additionally, compared to the time cost per iteration of single task model, the joint model does not take extra time. For DP task that shares the dataset and text features with QA task, it only needs an additional fully connected layer and a softmax layer as an activated function whose time cost is negligible. We combine the loss of DP and QA together to feed back to the model, so during the phases of feature extraction and back propagation, there will not be any extra cost.

5 Analysis

5.1 DP Improvement Analysis

Compared to single DP model, multi-tasking model can better parse the discourse structure. The possible reason is that QA task pays attention to extracting answer spans which requires the capacity to obtain salient information from utterances. Thus this relieves the problem of long distance dependency. This capacity also helps the DP task to resist the noise of long texts, and may have a positive impact on parsing nonadjacent utterance relationship.

To verify our speculation, we further extract and analyze the predictions of nonadjacent utterance relationship which is a relatively difficult part in DP task. We calculate the F1 scores of these predictions on both multi-tasking and single DP models on BERT_{wwm}. For link prediction, the F1 score of multi-tasking model is 56.2%, which is 1.4% higher than that of single DP task. For relationship prediction, the F1 score of multi-tasking model is 37.3%, which outperforms single DP task by 3.0%. We see that there are noticeable increases in both link and

Method		QA		DP	
		F1(%)	EM(%)	Link(%)	Relationship(%)
Human performance		80.2	64.3	-	-
Deep sequential(Li et al. (2020))		-	-	78.1	54.8
BERT _{base}	Li et al. (2020)	58.0	45.3	-	-
	QA-only	59.2	46.2	-	-
	DP-only	-	-	73.9	56.1
	Multi-task	61.3 (+2.1)	47.1 (+0.9)	75.9 (+2.0)	56.2 (+0.1)
BERT _{large}	Li et al. (2020)	65.5	51.8	-	-
	QA-only	64.0	49.6	-	-
	DP-only	-	-	81.0	61.5
	Multi-task	64.9 (+0.9)	50.6 (+1.0)	82.1 (+1.1)	62.0 (+0.5)
BERT _{wwm}	Li et al. (2020)	67.7	54.7	-	-
	QA-only	67.5	53.8	-	-
	DP-only	-	-	86.6	64.9
	Multi-task	68.4 (+0.9)	54.9 (+1.1)	88.1 (+1.5)	66.9 (+2.0)

Table 2: Results on Molweni dataset. Results except ours are from Li et al. (2020).

relationship predictions, which proves that with the help of QA task, DP task can better resist the noise of complex texts and predict nonadjacent utterance relationship more precisely.

5.2 QA Improvement Analysis

We divide the test set into three parts based on dialogue length: dialogues with less than or equal to 7 utterances (account for 40%), dialogues with 8 or 9 utterances (account for 31%) and dialogues with more than or equal to 10 utterances (account for 29%). We evaluate the QA-only model and MTL model respectively on these three subsets to further explore the impact of DP task on QA task. The results are shown in Figure 5. It shows that the QA-only performance on long dialogues is obviously worse than short ones. The reason could be the QA-only model can only obtain limited context information. When the distance between utterances is far, it can no longer pay enough attention to the relationship of these utterances which might actually be tightly interconnected.

It can be observed from Figure 5 that though the performances of MTL and QA-only on short dialogues have little difference, the MTL model can distinctly better handle longer dialogues. The results of MTL on long dialogues drop little compared to short dialogues, showing that MTL might benefit from the DP task which pays equal attention to related utterances even though they are far apart.

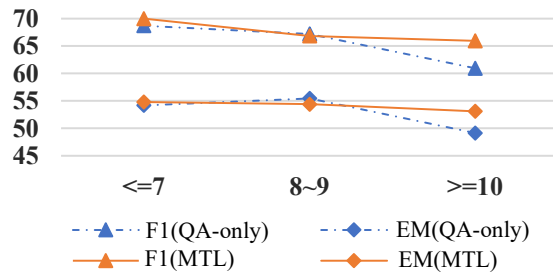


Figure 5: The results of dialogues with different numbers of utterances (on BERT_{wwm}).

5.3 Case Analysis

To further explore the effect of discourse structures on multi-party dialogue MRC, we compare all the QAPs predicted by multi-tasking model and single QA model respectively (on BERT_{wwm}). We intentionally fetch the answerable questions which are answered correctly on joint model while wrongly on single QA model. There are 99 such QAPs in the test set. Through artificial judging, we find 58 in 99 QAPs which confirms the help of DP to QA. For example, there is the following dialogue:

Suikwan: “do you know where i can get the linux drivers ?”
arkady: “apparently that is “ old and unsupported ” by d-link , and they do n’t have linux drivers”
arkady: “you can use ndiswrapper to wrap the windows drivers , then”

For the question *Where to get the linux drivers*, the joint model answer is *use ndiswrapper to wrap the windows drivers* which is exactly the same with gold answer while the answer of single QA model is *by d-link*. Owing to the discourse information, joint model puts more emphasis on the third turn because it captures the *QAP* relationship between the first and third utterances. By contrast, the QA-only task pays attention to traditional context, so it naturally extracts the answer from the adjacent utterance. These 58 in 99 cases are strong evidence for the importance of discourse parsing in multi-party dialogue MRC.

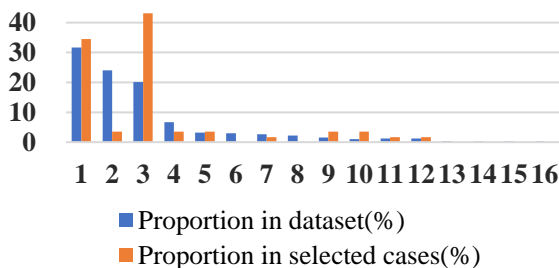


Figure 6: The proportion of main discourse relationships in Molweni dataset and the cases we choose. The relationship types name correspond to the types in Table 1.

To explore the detailed effects of different relationships, we calculated the proportion of each relationship in the 58 cases we choose. Figure 6 shows the result. We see that *QAP* accounts for a large proportion and makes a significant contribution to QA task. By contrast, *Clarification question* is not so important for QA. This inspires us that annotating the main contributive relationships like *QAP* precisely is very helpful to multi-party dialogue comprehension.

5.4 Error Analysis

In order to explore the potential improvement room, we statistically analyze the error cases of both single QA model and multi-tasking model. As shown in Figure 7, we calculate the proportion of each kind of questions in the error cases of these two models. Questions start with *what* account for the majority which is not surprising because most of the Molweni dataset is *what*-leading questions. It is worth noting that multi-tasking can better answer *who*-leading questions. The possible reason is that *who*-leading questions like *Who answered BrandonBolton ? fo-*

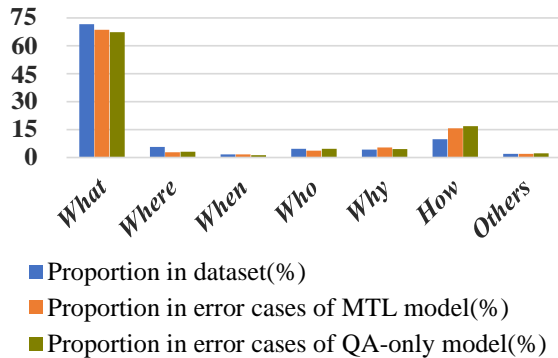


Figure 7: The proportion of question types in Molweni dataset, in the error cases of multi-tasking model and single QA model.

cuses on the relationship between speakers which is exactly what the discourse structures are for.

It is also distinct in Figure 7 that *how*-leading questions are challenging for both single QA and multi-tasking model. We attribute this difficulty to the too flexible and too diverse for the usage of *how*-leading questions. Compared to *how*, questions start with other adverbs such as *where*, *when* and other interrogative pronouns are more concrete and easier. This inspires us that syntactic analysis may have an impact on *how*-leading questions which worth a try.

6 Conclusion

In this paper, we are motivated to investigate the relationship between QA and DP tasks. To this end, we propose the first multi-task model for jointly performing QA and DP on one multi-party dialogue MRC to blend the discourse structures with answer extraction. Results indicate that our joint model indeed improves the performance of both QA and DP tasks, which proves that there exists a strong and positive correlation between these two tasks. A series of analyses are conducted to explore the contributing factors. For cases that the dialogue datasets might not have the corresponding discourse annotations, it is possible to apply off-the-shelf dialogue discourse parsing tools to obtain the discourse relationships (Ouyang et al., 2021), which is left for future work. In addition, it would be interesting to investigate graph networks to model complex QA based on discourse structures and improve the reasoning ability of dialogue systems.

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