MEETING ACTION ITEM DETECTION WITH REGULARIZED CONTEXT MODELING

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ABSTRACT

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Meetings are increasingly important for collaborations. Action items in meeting transcripts are crucial for managing post-meeting to-do tasks, which usually are summarized laboriously. The Action Item Detection task aims to automatically detect meeting content associated with action items. However, datasets manually annotated with action item detection labels are scarce and in small scale. We construct and release the first Chinese meeting corpus with manual action item annotations¹. In addition, we propose a Context-Drop approach to utilize both local and global contexts by contrastive learning, and achieve better accuracy and robustness for action item detection. We also propose a Lightweight Model Ensemble method to exploit different pre-trained models². Experimental results on our Chinese meeting corpus and the English AMI corpus demonstrate the effectiveness of the proposed approaches.

Index Terms— Action item detection, text classification, public meeting corpus, contextual information, model ensemble

1. INTRODUCTION

Due to technological advances and the pandemic, online meetings become more and more common for collaboration and information sharing. Automatic Speech Recognition (ASR) systems can convert audio recordings of meetings into transcripts. Many Natural Language Processing (NLP) tasks are conducted on meeting transcripts to automatically extract or generate important information such as summaries, decisions, and action items. Action item refers to a task discussed in the meeting and assigned to participant(s) and expected to complete *within a short time window* after the meeting [1]. The action item detection task aims to detect sentences containing information about actionable tasks in meeting transcripts. Action item detection could help users easily summarize meeting minutes, view and follow up on post-meeting to-do tasks.

Action item detection is usually modeled as a sentence-level binary classification task, to determine whether a sentence contains action items or not. Many previous works [2] explore machine learning methods and feature engineering on publicly available meeting corpora such as ICSI [3] and AMI [4]. Recently, with the success of the pretraining-finetuning paradigm and the revival of meeting-related research, approaches have been proposed based on pre-trained models [5], such as BERT [6] and ETC [7]. In addition, some works [8] focus on detecting each element of action items independently, including task description, ownership, timeframe, and agreement.

For action item detection, existing public meeting corpora, such as the AMI meeting corpus and the ICSI meeting corpus, are far

²https://github.com/alibaba-damo-academy/ SpokenNLP/tree/main/action-item-detection

[001] Speaker A: Hello everyone, welcome to the weekly meeting.
[002] Speaker A: Firstly, let's look at this tourist area development project.
[003] Speaker A: Tim, could you please tell us about the tourism area?
[035] Speaker B: There are some issues with our tourism development project.
[036] Speaker B: The positioning of the tourist area is still unclear
[267] Speaker A: OK, next time we meet, how about tomorrow?
[268] <i>Speaker B</i> : Okay, we will continue talking about the <i>project</i> tomorrow.
[269] Speaker A: Okay, we'll tentatively schedule at 3 pm, see you tomorrow.

Fig. 1. An example of action item detection. We show the speaker and sentence id, mark the action item, local context and global context. The local context provides the <u>timeframe</u> information. And the global context provides the *task description* information.

from adequate to evaluate advanced deep learning models. We obtain 101 annotated AMI meetings with 381 action items following previous works [5]. The ICSI meeting corpus comprises only 75 meetings without publicly available action item annotations. Therefore, we construct and make available a Chinese meeting corpus of 424 meetings with manual action item annotations on manual transcripts of meeting recordings (Table 1), to prompt research on action item detection.

Context understanding plays a critical role in various tasks on meeting transcripts. Prior works [5, 9] also explore context to improve action item detection performance. However, most methods concatenate the focus sentence with adjacent sentences (*local context*) and only achieve limited gains. As shown in Figure 1, relevant but non-contiguous sentences (*global context*) also provide useful information for action items. On the other hand, both local and global contexts may contain irrelevant information, which may distract the classifier. We propose a novel **Context-Drop** approach to improve context modeling with regularization so that the model could focus more on the current sentence, to better exploit relevant information, and be less distracted by irrelevant information in context.

In addition, we observe that the majority voting labels are usually correct during action item annotations. Inspired by this observation, we propose a **Lightweight Model Ensemble** method to improve performance by exploiting different pre-trained models while preserving inference latency.

The contributions of our work are as follows:

- We construct and make available a Chinese meeting corpus with action item annotations, to alleviate scarcity of resources and prompt related research. To the best of our knowledge, this is so far the largest meeting action item detection corpus.
- We propose a novel Context-Drop approach to improve context modeling of both local and global contexts with regularization, and achieve improvement in accuracy and robustness of action item detection for both Chinese and English meeting corpora.
- We propose a Lightweight Model Ensemble approach to integrate knowledge from different pre-trained models. We achieve improvement in accuracy while preserving inference latency.

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https://www.modelscope.cn/datasets/modelscope/ Alimeeting4MUG/summary

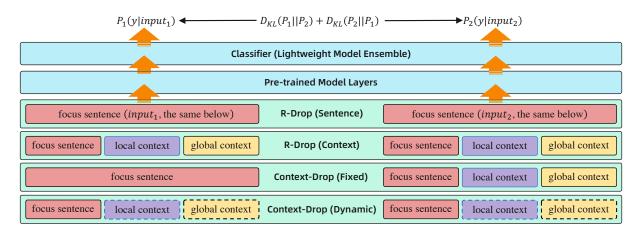


Fig. 2. Illustration of proposed Context-Drop (Section 3.1) and Lightweight Model Ensemble (Section 3.2) methods. Based on the pre-trained models, we propose the Context-Drop method to employ contextual information for action item detection. We utilize both local and global contexts to exploit as much relevant context as possible within the max sequence length of transformers. We also propose the Lightweight Model Ensemble to improve performance using different pre-trained models.

2. DATASETS

2.1. AMI Meeting Corpus

The AMI meeting corpus [4] has played an essential role in various meeting-related research. It contains 171 meeting transcripts and various types of annotations. Among 171 meetings, 145 meetings are scenario-based meetings and 26 are naturally occurring meetings. The AMI meeting corpus is a common dataset for benchmarking action item detection systems. Although there are no direct annotations for action items for this corpus, indirect annotations can be generated based on annotations of the summary. Following previous works [5], we consider dialogue acts linked to the action-related abstractive summary as positive samples for action item detection and otherwise negative samples. In this way, we obtain 101 annotated meetings with 381 action items.

2.2. Building A Large-scale Chinese Meeting Corpus

The two common datasets for action item detection, namely the AMI meeting corpus and ICSI meeting corpus, are both far from adequate for evaluating advanced deep learning models on action item detection. As described above, there are only 101 annotated meetings with 381 action items in the AMI meeting corpus. Another public meeting corpus, the ICSI meeting corpus, has action item annotations for 18 meetings [10] and is much smaller for action item detection research. Also, these annotations are no longer publicly available. Scarce and small-scale meeting datasets have hindered research on action item detection. To address this issue and prompt research on this topic, we construct and make available a Chinese meeting corpus, the AliMeeting-Action Corpus (denoted as AMC-A), with manual action item annotations on manual transcripts of meeting recordings. We extend 224 meetings previously published in [11] with additional 200 meetings. Each meeting session consists of a 15minute to 30-minute discussion by 2-4 participants covering certain topics from a diverse set, biased towards work meetings in various industries. All 424 meeting recordings are manually transcribed with punctuation inserted. Semantic units ended with a manually labeled period, question mark, and exclamation are treated as sentences for action item annotations and modeling.

We formulate action item detection as a binary classification task and conduct sentence-level action item annotations, i.e., sentences containing action item information (task description, time frame,

	AMC-A (ours)			AMI	
	All	Train	Dev	Test	
Total # Meetings	424	295	65	64	101
Total # Utterances	306,846	213,235	45,869	47,742	80,298
Total # Action	1506	1014	222	270	381
Kappa Coefficient	0.47	0.46	0.49	0.50	/
Avg. # Action per Meeting	3.55	3.44	3.42	4.22	3.77
Std. # Action per Meeting	3.97	3.98	3.35	4.41	1.95

 Table 1. Statistics of our Chinese AMC-A corpus and the English AMI meeting corpus studied in this work.

owner) as positive samples (labeled as 1) and otherwise negative samples (labeled as 0). As found in previous research and our experience, annotations of action items have high subjectivity and low consistency, e.g., only a Kappa coefficient of 0.36 on the ICSI corpus [10]. To ease the task, we provide detailed annotation guidelines with sufficient examples. To reduce the annotation cost, we first select candidate sentences containing both temporal expressions (e.g., "tomorrow") and action-related verbs (e.g., "finish"), and highlight them in different colors. Candidate sentences are then annotated by three annotators independently. During annotation, candidate sentences are presented with their context so that annotators can easily exploit context information. With these quality control methods, the average Kappa coefficient on AMC-A between pairs of annotators is 0.47. For inconsistent labels from three annotators, an expert reviews the majority voting results and decides on final labels. Table 1 shows that AMC-A has much more meeting sessions, total utterances, and total action items than the AMI meeting corpus and comparable avg. action items per meeting. To the best of our knowledge, AMC-A is so far the first Chinese meeting corpus and the largest meeting corpus in any language labeled for action item detection.

3. METHOD

We formulate action item detection as a binary classification task. Given an utterance X with its context C, the model predicts the label \hat{y} , i.e., whether X contains action items or not. Figure 2 illustrates the two proposed approaches, **Context-Drop** (Fixed and Dynamic) and **Lightweight Model Ensemble**. Context-Drop explores local and global contexts together with regularization. Lightweight Model Ensemble is an efficient approach for improving performance using different pre-trained models while preserving inference latency.

3.1. Context-Drop

Local and Global Context Coreferences and omission of information are quite common in multi-party meetings. Relevant and supporting information may appear in adjacent sentences or noncontiguous sentences. Context understanding has played a critical role in various understanding tasks in meetings, including sentencelevel action item detection. Relevant contexts are not limited to adjacent sentences (*local context*). In real meeting scenarios, topics are usually mixed, hence discussions of a certain action item may spread in the session. We denote these relevant but non-contiguous sentences by *global context* for action item detection.

Since the global context may be distant from the focus sentence, including all sentences between the global context and the focus sentence may exceed the max sequence length mandated by Transformer-based pre-trained language models (PLMs), such as BERT [6] and RoBERTa [12], due to their quadratic time and memory complexity to the input sequence length [13]. Hence, we employ a *context selection* method to retrieve the global context for each sentence. We use the cosine similarity of n-grams to measure the similarity between sentences in a document, following the ngram overlap method [14]. For each sentence, we select the top-k sentences with the highest similarity scores as its global context.

Context-Drop We propose a novel Context-Drop approach to improve context modeling for action item detection. Inspired by Contrastive Learning and R-drop [15], Context-Drop forces the prediction probability distributions of a single sentence and the sentence with its context to be consistent with each other. We hypothesize that Context-Drop could help the model to focus more on the current sentence, to better exploit relevant information and be less distracted by irrelevant information in context, which in turn could improve the robustness and performance of the model.

We propose two types of Context-Drop, namely, *Context-Drop* (*Fixed*) and *Context-Drop* (*Dynamic*). As shown in Figure 2, for Context-Drop (Fixed), *input*₁ is the focus sentence, *input*₂ is the sentence with its local/global context. For Context-Drop (Dynamic), the local/global context of the focus sentence is selected dynamically. Each sentence in context has a certain probability to be kept; otherwise, the sentence is dropped from context. Both Context-Drop variants force the prediction probability distributions for *input*₁ (denoted x) and *input*₂ (denoted x') to be as close as possible, by minimizing the bidirectional Kullback-Leibler divergence as in Eqn. 2. The overall loss is calculated as Eqn. 3, where α is a hyperparameter:

$$\mathcal{L}_{CE}^{i} = -\frac{1}{2} \log \left(P_1(y_i | x_i) \cdot P_2(y_i | x_i') \right) \tag{1}$$

$$\mathcal{L}_{\mathrm{KL}}^{i} = \frac{1}{2} \left(\mathcal{D}_{\mathrm{KL}} \left(P_{1}(y_{i}|x_{i}) || P_{2}(y_{i}|x_{i}') \right) \right)$$
(2)

$$+ \mathcal{D}_{\mathrm{KL}} \left(P_2(y_i | x_i^{\cdot}) || P_1(y_i | x_i) \right) \right)$$
$$\mathcal{L}^i = \mathcal{L}^i_{\mathrm{CE}} + \alpha \cdot \mathcal{L}^i_{\mathrm{KL}} \tag{3}$$

Context-Drop (Dynamic) makes the contrast between samples more flexible. When all contexts are dropped for both $input_1$ and $input_2$, Context-Drop (Dynamic) works equivalently to the *R*-Drop (Sentence) method in Figure 2. When all contexts are kept for both $input_1$ and $input_2$, the approach works equivalently to *R*-Drop (Context). When all contexts are dropped for $input_1$ and all contexts are kept for $input_2$, the approach works equivalently to Context-Drop (Fixed). Hence, Context-Drop (Dynamic) could be considered as a generalization of the other three methods in Figure 2.

Model	Modeling Task	AMC-A \mathbf{F}_1
BERT Longformer StructBERT	sentence classification sequence labeling sentence classification	$\begin{array}{c} 64.76 {\pm} 0.98 \\ 65.35 {\pm} 1.33 \\ \textbf{67.84} {\pm} 1.20 \end{array}$

Table 2. Positive F_1 on the **Test** set of our AMC-A corpus using different pre-trained language models with different modeling tasks.

Input Method	AMC-A \mathbf{F}_1	AMI \mathbf{F}_1
sentence	$67.84{\pm}1.20$	38.67±1.25
w/ R-Drop	$68.77{\pm}0.82$	$39.26 {\pm} 1.70$
+ local context	68.50±1.21	41.03±1.42
w/ R-Drop	$68.79 {\pm} 0.42$	42.72 ± 0.74
w/ Context-Drop _{fixed}	$69.15 {\pm} 0.91$	43.12 ± 0.74
w/o KL loss	68.23 ± 1.11	40.71 ± 1.78
w/ Context-Drop _{dynamic}	$69.53 {\pm} 0.75$	$42.05 {\pm} 0.31$
w/o KL loss	$67.97{\pm}0.53$	$41.44{\pm}2.29$
+ global context	67.99±1.86	$35.82{\pm}1.11$
w/ R-Drop	$69.80{\pm}1.14$	$37.88 {\pm} 1.04$
w/ Context-Drop _{fixed}	$69.07 {\pm} 0.57$	$39.23 {\pm} 0.73$
w/ Context-Drop _{dynamic}	$\underline{70.48}{\pm}0.63$	$41.25{\pm}1.76$
+ local & global context	69.09±1.23	41.31±1.51
w/ R-Drop	68.72 ± 1.04	$40.75 {\pm} 1.28$
w/ Context-Drop _{fixed}	$69.28{\pm}0.95$	$38.66 {\pm} 0.77$
w/ Context-Drop _{dynamic}	70.82±1.33	$41.50{\pm}1.52$

Table 3. Positive F_1 on the **Test** sets of our AMC-A corpus and the AMI meeting corpus. All experiments fine-tune the pre-trained Chinese and English StructBERT models respectively. We compare the performance of different input methods (the single focus sentence or the focus sentence with its local/global context) and different training loss, including the standard CE loss by default, with R-Drop, and with the two variations of Context-Drop (Section 3.1).

Model Layers	Pooler Layer	AMC-A F_1
StructBERT	StructBERT RoBERTa	$\begin{array}{c} 67.84{\pm}1.20\\ 68.36{\pm}0.93\end{array}$
RoBERTa	RoBERTa StructBERT	$66.87 {\pm} 0.44$ $67.25 {\pm} 0.93$

Table 4. Positive F_1 on the **Test** set of our AMC-A corpus, from fine-tuning pre-trained StructBERT and RoBERTa models and the hybrid model using Lightweight Model Ensemble (Section 3.2).

3.2. Lightweight Model Ensemble

During action item annotation, we observe that for inconsistent labels from three annotators, the majority voting results are usually correct despite the relatively low inter-annotator agreement, as the expert only modifies 5%-10% of the majority voting labels. Inspired by this observation, we explore model ensemble, a common approach for improving performance. In this work, we propose a Lightweight Model Ensemble approach, which improves accuracy while preserving inference latency. Conventionally, we initialize each layer of a classification model with parameters from the same pre-trained model. In our Lightweight Model Ensemble approach, we initialize encoder layers of the action item detection model θ_C using parameters from one pre-trained model θ_A and initialize the

pooler layer of θ_C using the pooler layer parameters from another pre-trained model θ_B . We then fine-tune θ_C with the cross-entropy loss on the meeting corpus. In this way, we integrate knowledge from different pre-trained models efficiently, without increasing the overall number of parameters and slowing down inference.

4. EXPERIMENTS

4.1. Datasets and Metrics

We use both the AMI meeting corpus and our AMC-A corpus. We partition the AMI meeting corpus following the official scenarioonly dataset partitioning³. We partition AMC-A into train/dev/test sets with a ratio of 70:15:15, respectively. Considering the sparsity of positive samples, we report positive F_1 as the evaluation metric.

4.2. Baseline and Implementation Details

To evaluate our proposed methods on the AMC-A and AMI datasets, we use the following strong baseline pre-trained models, namely, BERT [6]⁴, RoBERTa [12], StructBERT [16]⁵, and Longformer [17] which provides efficient long-sequence modeling. For RoBERTa, We use the pre-trained Chinese RoBERTa-wwm-ext model[18]⁶. For Longformer, we use the pre-trained Erlangshen-Longformer- $110M[19]^7$ to model action item detection as a sequence labeling task and use a fixed sliding window with size 4096 and allow one sentence overlap. The sentence labeling task takes multiple sentences as input and outputs the probabilities for every sentence. For BERT, StructBERT, and RoBERTa, we model action item detection as a sentence classification task and truncate input to 128 tokens. The sentence classification task takes a sentence as input and outputs the probabilities for the sentence. We compare our Context-Drop approach to R-Drop [15]. R-Drop forces the predicted probability distribution of the same sample after two dropouts to be as close as possible. We compare the performance of R-Drop with sentencelevel inputs and context-level inputs (Figure 2).

We use TensorFlow and PyTorch to implement all models. All PLMs used are of BERT base size. The batch size is 32 and the dropout rate is 0.3. For each experiment in this paper, we run 5 times with different random seeds; for each run, we conduct a grid search among $\{1e - 5, 2e - 5\}$ learning rate and $\{2, 3\}$ epochs on the dev set. We then report the mean and standard deviation of the best results from 5 runs. The weight α of KL divergence loss is set to 4.0 for R-Drop and 1.0 for Context-Drop by optimizing positive F_1 on the dev set. For each sentence, we use its preceding sentence and following sentence as *local context*, and select the top-2 most similar sentences to this sentence as *global context* (see Section 3.1 for details). The probability to keep contextual sentences is 50% for *local* or *global contexts*, and 70% for *local* & *global contexts*. Following setups in prior works, no sampling methods are applied.

4.3. Results and Analysis

As shown in Table 2, we compare different PLMs with different modeling tasks. When modeling action item detection as a sentence classification task, StructBERT outperforms BERT with a remarkable gain of +3.08 on positive F₁. The word structural pretraining objective of StructBERT reconstructs tokens in the correct order from the shuffled trigrams. This could improve its robustness to disordered sentences, which is quite common in spoken languages, and in turn improve its performance of meeting action item

⁴https://github.com/google-research/bert

structbert_backbone_base_std

⁶https://github.com/ymcui/Chinese-BERT-wwm

detection. We formulate action item detection as a sequence labeling task to exploit the advantage of Longformer in long-sequence modeling. However, we only observe limited improvement from Longformer over BERT, 0.59 gain on positive F_1 . Therefore, we formulate action item detection as a sentence classification task and use StructBERT as the pre-trained model for evaluating Context-Drop.

As shown in Table 3, based on the baseline StructBERT, we compare various contrastive learning methods using different contexts (Figure 2). On AMC-A, when not using contrastive learning methods, i.e., no w/ R-Drop nor w/ Context-Drop, the baseline using both local and global context performs the best (69.09), followed by the baseline using the local context (68.50). We observe the same trend on AMI. This indicates that adjacent contextual sentences do provide useful information. Global context provides complementary information and a combination of global and local context achieves further improvement. On AMC-A, when using different contrastive learning methods, the configuration of using the focus sentence and local & global context as input with Context-Drop_{dynamic} achieves the best performance (70.82), outperforming the baseline using the sentence as input without contrastive learning (67.84) by +2.98 absolute on positive F1, and also outperforming R-Drop (68.72) by +2.10 absolute gain. On AMI, sentence+local context w/ Context-Drop_{fixed} (43.12) also outperforms the baseline sentence input (38.67) and R-Drop (42.72). These results confirm our hypothesis that Context-Drop could help the model to focus more on the current sentence, exploit relevant information in context and be less distracted by irrelevant information. Moreover, a reduction in the standard deviations shows that Context-Drop improves the stability and robustness of the model. For different contexts, Context-Drop_{dynamic} outperforms Context-Drop_{fixed} in most cases, which suggests that the flexible and dynamic contrastive learning method can achieve better performance.

We also conduct ablation analysis on Context-Drop, as in the second group of Table 3. Without the regularization loss of KL divergence (denoted KL loss), Context-Drop can be regarded as a data augmentation method using fixed or dynamically selected context. On AMC-A and AMI, for both Context-Drop_{fixed} and Context-Drop_{dynamic}, w/o KL loss degrades the performance, which indicates contrastive learning is important for gains. With the regularization loss, the model could better focus on the current sentence and be less distracted by irrelevant information in context.

As shown in Table 4, we compare the performance of applying Lightweight Model Ensemble integrating various pre-trained models using the sentence input. StructBERT encoder with RoBERTa pooler layer parameters achieves +0.52 absolute gain and RoBERTa encoder with StructBERT pooler layer parameters achieves +0.38 absolute gain. These results show that Lightweight Model Ensemble could integrate knowledge from different models and achieve better performance without increasing the overall number of parameters.

5. CONCLUSION

We construct and make available the first Chinese meeting corpus with action item annotations, to alleviate the scarcity of resources and prompt research on meeting action item detection. We propose Context-Drop to exploit both local and global contexts with regularization. On both our meeting corpus and English AMI meeting corpus, Context-Drop improves the accuracy and robustness of action item detection. We also propose Lightweight Model Ensemble and achieve improvement. In future work, we plan to refine Lightweight Model Ensemble and investigate its efficacy on other tasks as well as combining Context-Drop and Lightweight Model Ensemble.

³https://groups.inf.ed.ac.uk/ami/corpus/ datasets.shtml

⁵https://modelscope.cn/models/damo/nlp_

⁷https://github.com/IDEA-CCNL/Fengshenbang-LM

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