OVERVIEW OF THE ICASSP 2023 GENERAL MEETING UNDERSTANDING AND GENERATION CHALLENGE (MUG)

Qinglin Zhang¹, Chong Deng¹, Jiaqing Liu¹, Hai Yu¹, Qian Chen¹ Wen Wang¹, Zhijie Yan¹, Jinglin Liu², Yi Ren², Zhou Zhao²

¹ Speech Lab of DAMO Academy, Alibaba Group ² Zhejiang University

¹{qinglin.zql, dengchong.d, mingzhai.ljq, yuhai.yu}@alibaba-inc.com ¹{tanqing.cq, w.wang, zhijie.yzj}@alibaba-inc.com ²{jinglinliu, rayeren, zhaozhou}@zju.edu.cn

ABSTRACT

ICASSP2023 General Meeting Understanding and Generation Challenge (MUG) focuses on prompting a wide range of spoken language processing (SLP) research on meeting transcripts, as SLP applications are critical to improve users' efficiency in grasping important information in meetings. MUG includes five tracks, including topic segmentation, topic-level and session-level extractive summarization, topic title generation, keyphrase extraction, and action item detection. To facilitate MUG, we construct and release a largescale meeting dataset, *the AliMeeting4MUG Corpus.* We review the dataset, track settings and baselines, and summarize the challenge results and major techniques used in the submissions.

Index Terms— Keyphrase Extraction, Topic Segmentation, Title Generation, Summarization, Action Item Detection

1. INTRODUCTION

Spoken language processing (SLP) applications are crucial for distilling, organizing, and prioritizing information and significantly improves users' efficiency in grasping important information in meetings [1]. Meetings pose two great challenges to SLP. First, meeting transcripts exhibit a wide variety of spoken language phenomena, such as disfluencies, grammar errors, and incomplete/fragmented sentences due to speaker interactions, which causes drastic differences from written texts, the majority of training data of NLP models, hence leads to dramatic performance degradation. Second, meeting transcripts are usually long-form documents with several thousand words or more, challenging to mainstay Transformerbased models. Publicly available meeting corpora supporting SLP research are limited and on small scale, severely hindering advances of meeting SLP [1]. To fuel research on meeting SLP, we launch **ICASSP2023** General Meeting Understanding and Generation challenge (MUG)¹. To facilitate MUG, we construct and release the AliMeeting4MUG Corpus (AMC). To the best of our knowledge, AMC is the largest meeting corpus in scale and facilitates the most SLP tasks [1]. MUG includes five tracks: Track1 Topic Segmentation (TS), Track2 Topic-level and Session-level Extractive Summarization (ES), Track3 Topic Title Generation (TTG), Track4 Keyphrase Extraction (KPE), and Track5 Action Item Detection (AID). We review the dataset, tracks and baselines, and summarize challenge results and major techniques used in submissions.

2. DATASET, TRACK SETTING AND BASELINES

Dataset and Tracks Our paper [1] describes the dataset and tracks for MUG in detail. AMC² includes 654 collected Mandarin meetings with each meeting consisting of a 15- to 30-minute discussion by 2-4 participants covering diverse topics. The avg. session length is 10,772.5 tokens, showing the long-form document challenge. The avg. # turns per session is 376.3, indicating frequent speaker interactions. We create manual SLP annotations on manual transcripts of meeting recordings with manually inserted punctuation and manual speaker labels. Details of SLP annotations and analyses are in [1]. 524 meetings are manually annotated for all 5 SLP tasks (TS,ES, TTG, KPE, AID) and the rest 130 meetings are manually annotated with only TS. For Track2-5, we partition the 524 meetings with all 5 SLP annotations into 295 sessions for Train, 65 sessions for Dev, 82 sessions for Stage1 test set (exceptTS-Test1) and 82 sessions as Stage2(Final) test set (exceptTS-Test2). For Track1, we use the same Train and Dev sets and partition the 130 meetings with only TS labels into 65 sessions as TSonly-Test1 and 65 sessions as TSonly-Test2. Track1-TS requires segmenting the manual transcripts of a session into a sequence of non-overlapping, topically coherent segments. For evaluation, we use positive F_1 , P_k , and WinDiff(WD). The leaderboard score is computed as $0.5 \times \text{positive}F_1 + 0.25 \times$ $(1 - P_k) + 0.25 \times (1 - WD)$. Track2-ES requires extracting key sentences for each reference topic segment and the entire session. We report both average and best ROUGE-1,2,L scores based on the 3 references for topic- and session-level ES. The leaderboard score is the average of these 12 scores. Track3-TTG requires generating an informative and concise title for each reference topic segment. We report both average and best ROUGE-1,2,L scores based on the 3 references and the leaderboard score is the average of the 6 scores. Track4-KPE requires extracting top-K keyphrases from a session that can reflect its main content. We evaluate exact F1 and partial F_1 at top-K (K = 10, 15, 20) between predicted KPs and reference KPs, and the leaderboard score is the average of the 6 scores. Track5-AID requires detecting sentences containing information about actionable tasks. We report positive precision, recall, and F_1 and the leaderboard score is positive F_1 .

Baseline Systems We build baseline systems³ tackling the two key challenges of meeting SLP. We model TS and ES as sequence labeling tasks and AID as sentence classification task and compare BERT-

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¹https://modelscope.cn/headlines/article/52

²https://modelscope.cn/datasets/modelscope/Alimeeting4MUG/su ³https://github.com/alibaba-damo-academy/SpokenNLP

Track 1 Topic Segmentation (TS)								
Model	positive F ₁	$1 - p_k$	1-WD					
PoNet	$23.2_{\pm 0.51}$	$0.589_{\pm 0.012}$	0.569 ± 0.019					
Track 2 Extractive Summarization (ES) (AVG)								
Model	R-1 Avg./Best	R-2 Avg./Best	R-L Avg./Best					
PoNet	$55.73 \pm 0.39/63.87 \pm 0.62$	$33.66 \pm 0.55 / 44.87 \pm 0.75$	$43.11 \pm 0.89/54.82 \pm 0.96$					
Topic-level ES								
Model	R-1 Avg./Best	R-2 Avg./Best	R-L Avg./Best					
PoNet	$54.05_{\pm 0.73}/66.60_{\pm 0.91}$	$36.87_{\pm 0.84}/53.30_{\pm 1.31}$	$47.39_{\pm 0.89}/63.06_{\pm 1.15}$					
Session-level ES								
Model	R-1 Avg./Best	R-2 Avg./Best	R-L Avg./Best					
PoNet	$57.41 \pm 0.38/61.14 \pm 0.72$	$30.45 \pm 0.48/36.43 \pm 0.76$	$38.82 \pm 0.93/46.57 \pm 1.08$					
Track 3 Topic Title Generation (TTG)								
Model	R-1 Avg./Best	R-2 Avg./Best	R-L Avg./Best					
PALM	$28.44 \pm 0.40/40.74 \pm 0.49$	$15.26 \pm 0.31/24.54 \pm 0.29$	$26.74 \pm 0.41/39.04 \pm 0.50$					
Track 4 Keyphrase Extraction (KPE)								
Model	Exact/Partial F1@10	Exact/Partial F1@15	Exact/Partial F1@20					
Structbert-NER	$18.3_{\pm 0.6}/32.0_{\pm 0.4}$	$23.2_{\pm 0.8}/37.6_{\pm 0.1}$	$26.6_{\pm 0.4}/41.2_{\pm 0.3}$					
Track 5 Action Item Detection (AID)								
Model	positive P	positive R	positive F1					
Structbert	$62.73_{\pm 1.39}$	$71.1_{\pm 0.35}$	$66.65_{\pm 0.87}$					

Table 1. Baseline performance on the *TSonly-Test1* set for Track1 and *exceptTS-Test1* set for Track2-5. Each mean and std are computed on results from 5 runs with different random seeds.

base⁴, StructBERT-base [2], Longformer-base [3]⁵ with linear complexity, and PoNet-base [4]. PoNet [4] uses multi-granularity pooling and fusion for long sequence modeling and provides a linearcomplexity drop-in replacement of self-attention. PoNet achieves a good balance between complexity and transfer learning capability [4]. StructBERT [2] adds auxiliary pre-training objectives into BERT, which improve robustness to noisy word orders in spoken language. We find PoNet-based systems performs best on TS and ES and StructBERT-based system performs best on AID. Our TTG baseline uses the pre-trained PALM model [5], which jointly pretrains autoencoder and autoregressive language model hence better serves generation tasks. The KPE baseline uses StructBERT with CRF for sequence labeling, significantly outperforming the unsupervised YAKE. Table 1 reports the baseline results.

3. SUMMARY OF TRACK RESULTS

Overall Results 300+ developers participated in the MUG challenge and 47 teams submitted Stage2 (Final) evaluation submissions. Table 2 reports leaderboard scores from Top-3 teams and our baselines on *TSonly-Test2* for Track1 and *exceptTS-Test2* sets for Track2-5.

Rank	Track 1	Track2	Track3	Track4	Track5
1	48.84	52.56	33.77	45.07	63.89
2	46.52	51.69	33.71	42.59	63.49
3	42.92	49.58	31.98	38.43	61.31
baseline	41.01	49.57	27.50	41.48	61.15

Table 2. Results from Top-3 teams and our baselines on MUG Track1-5.

Tackle Two Key Challenges We find the top performing teams all develop approaches to address the two key challenges of meeting SLP and these approaches yield most notable gains. (1) *To improve robustness to spoken language phenomena*, ES #1 team [6] improves performance by exploring token-masking and span-masking with different masking rates for post-training DeBERTa. Many teams also improve performance on spoken language with preprocessing to remove disfluency and uninformative short sentences.

(2) To better model long-form documents, TS #1 team [7] achieves significant gains from modeling document-level context via intersentence Transformer on sentence representations over PoNet. TS #2 team aggregates sentence representations in a paragraph and models inter-paragraph relations. ES #1 team achieves superior performance through multi-task learning of topic- and session-level extractive summarization based on DeBERTa, as DeBERTa can handle input length up to 4096 tokens. ES #2 team designs a hybrid PoNet+TransformerEncoder model, achieving a better balance of accuracy and efficiency over PoNet.

Explore Additional Data (1) Data Augmentation. TS #1 team ensures consistent length distribution between their synthesized meeting data and AMC. TS #2 team uses Maximum Mean Discrepancy Loss to ensure consistent distribution between AMC and their augmented data. (2) Explore Written Text Data. TTG #1 team [8] develops multi-stage training to leverage knowledge from large models and additional data. They first pre-train the encoder-decoder CPTlarge model on the news title generation data, then triple AMC Train by using each of the 3 annotations as target and use the expanded data to fine-tune CPT-large from Stage1, and finally conduct joint fine-tuning and distillation with teacher as CPT-large from Stage2 and student as CPT-base pre-trained using the news title generation data. The Stage3 fine-tuning data is constructed on AMC Train by selecting the title most similar to the other 2 titles as target. TTG #2 team also first trains a pre-trained encoder-decoder model with two written text summarization corpora then fine-tunes with AMC.

Other Techniques (1) Many teams use focal loss to address *imbalanced labeled data*. (2) Many teams adopt adversarial training such as FGM to improve *generalizability*. ES #1 team improves generalizability using stochastic weight averaging on linear layers. (3) *Taskspecific*. KPE #1 team [9] jointly optimizes focal loss and regression loss (to fit model predicted scores to scores assigned by a W2NER module). Inspired by observations that most actionable items are acknowledged by other participants, AID #1 team [10] expands model input with sentences and speaker labels from adjacent context.

4. CONCLUSION

We provide an overview of ICASSP2023 General Meeting Understanding and Generation Challenge (MUG). We find approaches to address the two key challenges to meeting SLP yield most notable performance gains. Exploring additional data, handling imbalanced labels, improving generalizability, and other task-specific approaches also contribute to performance gains.

5. REFERENCES

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