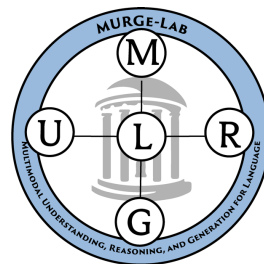


MeetingQA: Extractive Question-Answering on Meeting Transcripts

Archiki Prasad¹, Trung Bui², Seunghyun Yoon²,
Hanieh Deilamsalehy², Franck Dernoncourt², Mohit Bansal¹

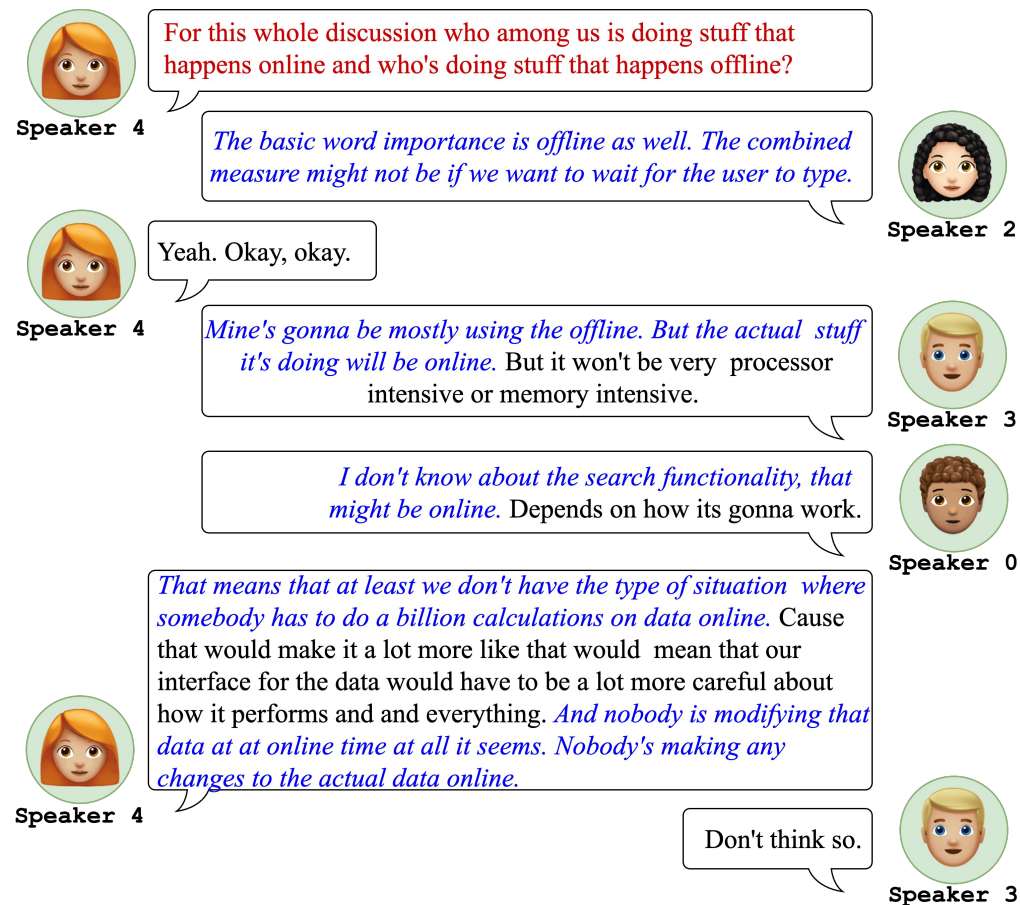
¹UNC Chapel Hill, ²Adobe Research



Motivation

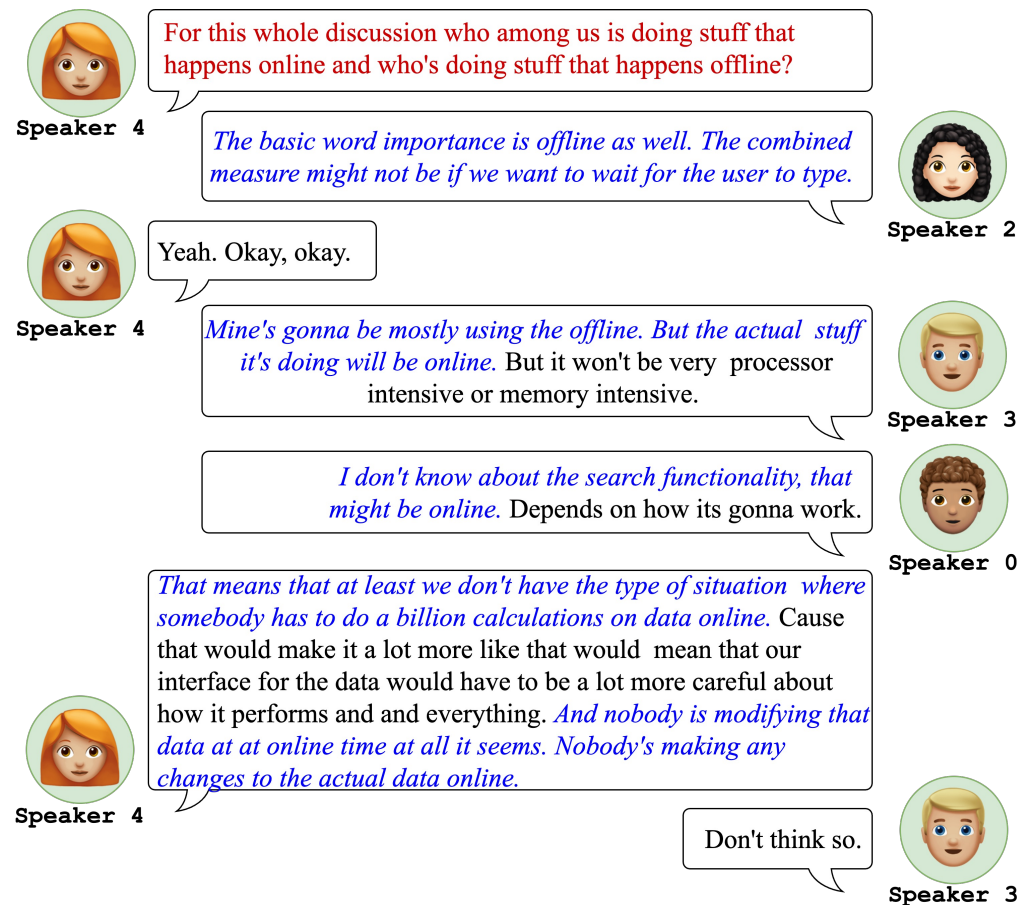
- Millions of meetings take place everyday worldwide
- Vast amounts of meeting transcripts
- What makes meeting transcripts unique?
 - Long documents
 - Domain-specific and information-rich
- Prior works focus on summarization and extracting action items
 - Under-utilize significant QA component in meeting discussions

MeetingQA: Introduction



- Extractive QA dataset based on *questions asked by participants in a meeting* and corresponding answer sentences

MeetingQA: Introduction



- Extractive QA dataset based on *questions asked by participants in a meeting* and corresponding answer sentences
- Why choose questions asked by participants?
 - Questions are longer, open-ended, and discussion-seeking
 - Rhetorical questions, multi-speaker, and multi-span answers

MeetingQA: Data Collection



Public transcripts from AMI corpus

~100 hours of manually
transcribed multi-party
meetings



Question Selection

Based on punctuation and
length of question



Answer Annotation

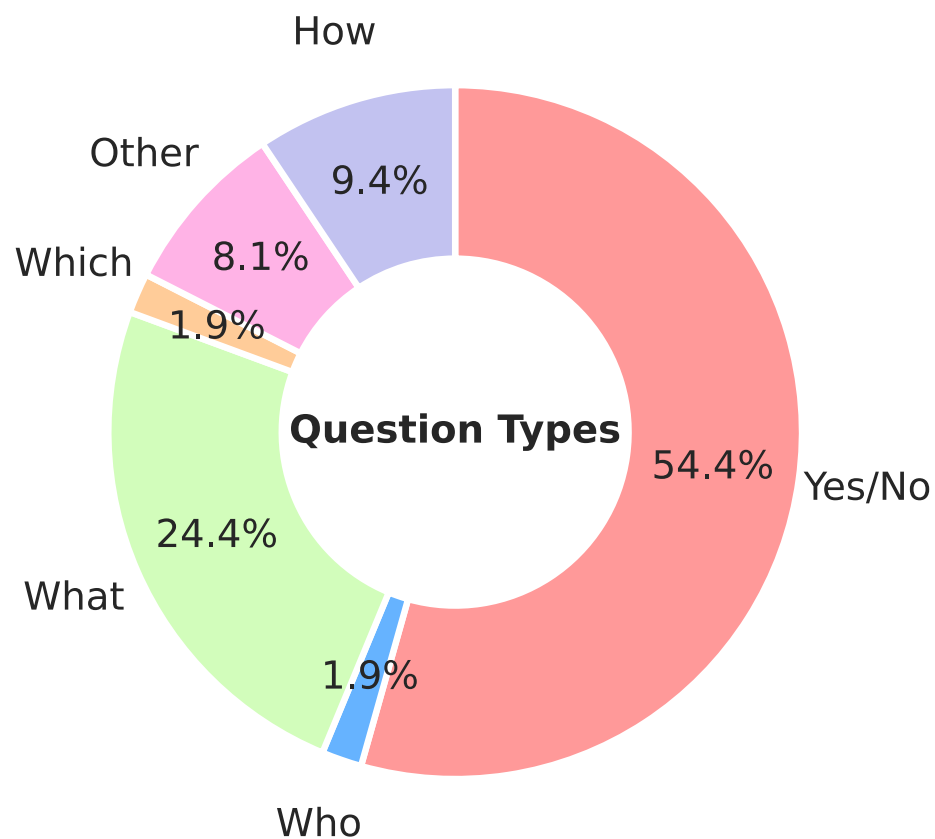
Recruit annotators to label
sentences in answer span
High inter-annotator agreement:
Krippendorff's $\alpha = 0.73$

MeetingQA: Dataset Analysis

	Train	Dev	Test
Number of Meetings	64	48	54
Number of Questions	3007	2252	2476
w/ No Answer	956	621	764
w/ Multi-Span Answers	787	548	663
w/ Multi-Speaker Answers	1016	737	840
Avg. Questions per Meeting	46.98	46.92	45.85

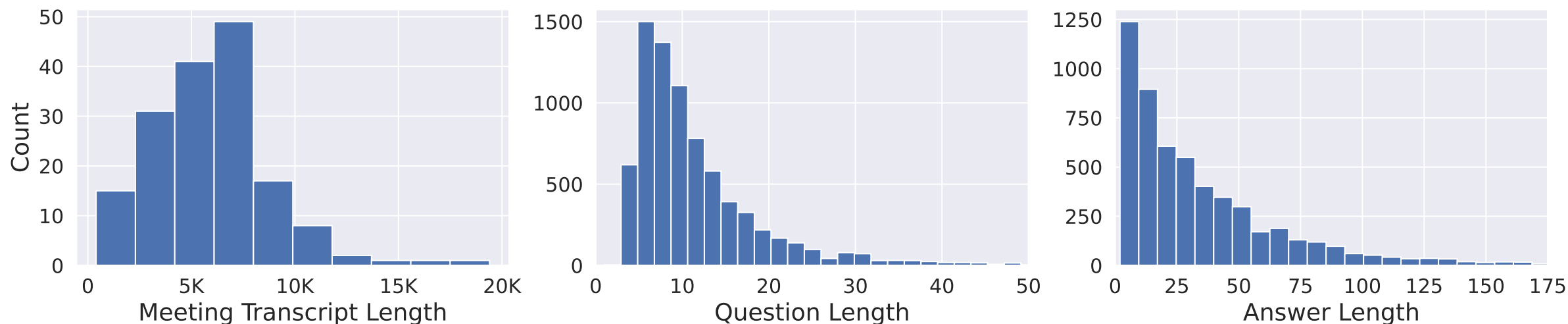
- Total of 7,735 questions from 166 different meetings split across train, dev, and test sets
- Statistics
 - Unanswerable Questions: 30%
 - Multi-span (non-consecutive sentences) answers: 40%
 - Multi-speaker answers: 48%

MeetingQA: Dataset Analysis



- Yes/no questions are information-seeking and detailed responses
- 50% questions are opinion-seeking
- 20% questions are framed rhetorically
- 70% of multi-speaker answers contain some disagreement

MeetingQA: Dataset Analysis



- Avg. Transcript: 5.9K words, Question: 12 words, and Answer: 35 words
- High human performance: F1 = 84.6

Methods



Context-retrieval for short-context models

Retrieve relevant segment of meeting transcript as context



Single-span models

Single 'super' span: first to last relevant sentence in span



Multi-span models

Using token classification models
- *I* tag: in answer span
- *O* tag: outside answer span



Silver data augmentation

Automatically annotated answer spans for questions from interviews in MediaSum dataset

Experimental Results: Finetuned

	Model	Overall F1	No Ans. F1	Answerable F1		
				All	M-Span	M-Speaker
S_S	RoBERTa-base	56.5	41.0	63.1	60.8	64.1
	Longformer-base	55.6	46.1	59.9	55.3	59.4
M_S	RoBERTa-base	54.0	41.1	59.8	58.2	60.9
	Longformer-base	53.8	39.4	60.3	58.8	62.0
Human Performance		84.6	80.7	86.3	88.1	87.7

Finetuned Performance

- ≥ 25 F1 points gap with human performance

Experimental Results: Finetuned

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- Short-context models slightly outperform long-context

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Finetuned Performance

- ≥ 25 F1 points gap with human performance
- Short-context models slightly outperform long-context
- Multi-span models have slightly less or comparable performance than single-span models

Experimental Results: Zero-shot

Model	Inter. Data	Overall F1
RoBERTa-base	SQuADv2 + silver	27.9 34.6
Longformer-base	SQuADv2 + silver	15.1 32.5
FLAN-T5 XL	—	33.8
FLAN-T5 XL (self ans)	—	34.0
Human performance	—	84.6

Zero-shot Performance

- ~50 F1 points gap with respect to human performance

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Zero-shot Performance

- ~50 F1 points gap with respect to human performance
- Silver data augmentation is effective

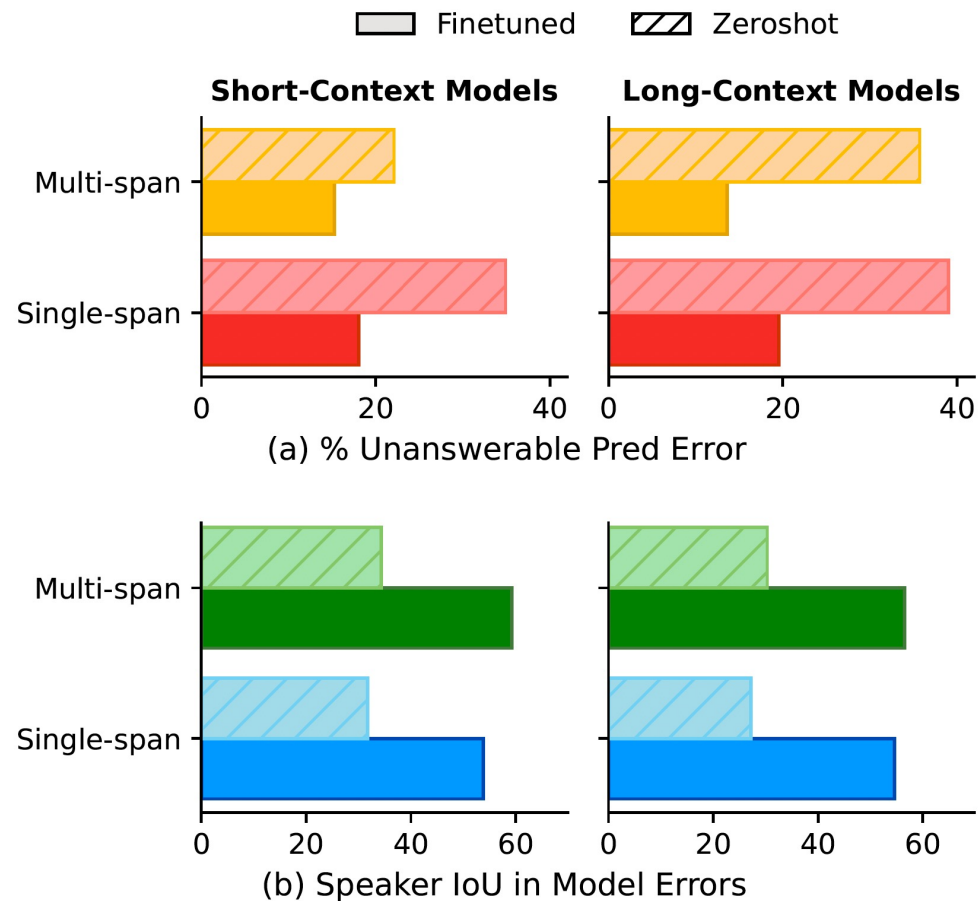
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Human performance	—	84.6

Zero-shot Performance

- ~50 F1 points gap with respect to human performance
- Silver data augmentation is effective
- Larger instruction tuned models yield comparable performance

Experimental Results: Error Analysis



- Models struggle at identifying rhetorical questions, especially in zero-shot setting
- Single-span predictions contain more irrelevant sentences
- Models struggle to identify which speakers answer a question, especially in zero-shot setting

Takeaways

- MeetingQA is an **interesting QA dataset** based on open-ended and discussion-heavy questions asked during meetings
- MeetingQA is **challenging for existing QA models** which lag behind human performance significantly
 - 25 F1 point gap in finetuned setting
 - 50 F1 point gap in zero-shot setting

Thank you for listening!

Project Page: <https://archiki.github.io/meetingqa.html>

Contact: archiki@cs.unc.edu