IAM: A Comprehensive and Large-Scale Dataset for Integrated Argument Mining Tasks

Liying Cheng*^{1,2} Lidong Bing^{†1} Ruidan He¹ Qian Yu^{‡3} Yan Zhang^{‡4} Luo Si¹

¹DAMO Academy, Alibaba Group ²Singapore University of Technology and Design

³The Chinese University of Hong Kong ⁴ National University of Singapore

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발제자 : 이다현

HUMANE Lab

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Motivation

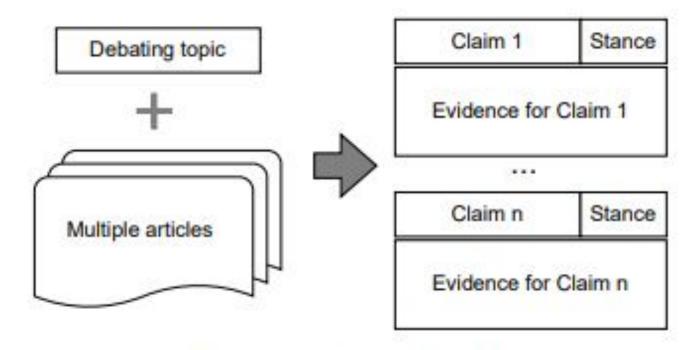


Figure 1: A flow chart showing the debating preparation process.

Motivation



15분 만에 토론 준비 끝... 토론하는 AI 등장

옷 정윤아 기자 ② 입력 2021.03.20 14:53 🗏 댓글 0 ♡ 좋아요 0











IBM, 인간과 토론 가능한 AI기반 시스템 개발 토론 승패보다는 복잡다기한 인간 언어 세계 이해가 목표 아마존 대화형 AI 챌린지 태스크봇(TaskBot) 챌린지 시작

Motivation

Existing argument mining (AM) tasks:

- Claim Extraction
- Stance Classification
- Evidence Extraction

☐ These essential elements are mutually reinforcing in the debating preparation process

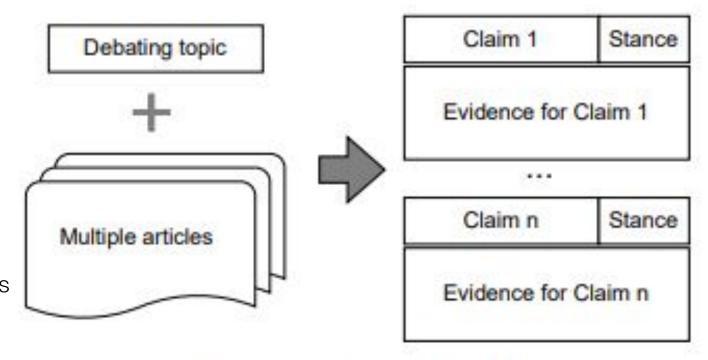


Figure 1: A flow chart showing the debating preparation process.

Goal:

More Integrated tasks

IAM Dataset - Data Collection

Online forums

123 debating topics

NLTK

English Wikipedia

1010 articles

69666 sentences

IAM Dataset - Data Annotation

Claim & Evidence

A claim is a general and concise statement that directly supports or contests the given topic. (Levy et al., 2014).

	Topic: Will artificial intelligence replace humans	Claim	Stance
1	Job opportunities will grow with the advent of AI; however, some jobs might be lost because AI would replace them.	C_1	+1
3	Any job that involves repetitive tasks is at risk of being replaced. In 2017, Gartner predicted 500,000 jobs would be created because of AI, but also predicted that up to 900,000 jobs could be lost because of it.	C_2	+1
6	The number of industrial robots has increased significantly since the 2000s. The low operating costs of robots make them competitive with human workers. In the finance sector, computer algorithms can execute stock trades much faster than a human, needing only a fraction of a second. As these technologies become cheaper and more accessible, they will be implemented more widely, and humans might be increasingly replaced by AI.	C_3	 +1
8	According to Harvard Business Review, most operations groups adopting RPA have promised their employees that automation would not result in layoffs.	C_4	-1
9	AI is incredibly smart, but it will never match human creativity.	C_5	-1

IAM Dataset - Data Annotation

Claim & Stances Evidence

A piece of evidence is a text segment that directly supports a claim in the context of the topic (Rinott et al. 2015).

	Topic: Will artificial intelligence replace humans	Claim	Stance	Evidence
1	Job opportunities will grow with the advent of AI; however, some jobs might be lost because AI would replace them.	C_1	+1	
- 2 -	Any job that involves repetitive tasks is at risk of being replaced.			
3	In 2017, Gartner predicted 500,000 jobs would be created because of AI, but also predicted that up to 900,000 jobs could be lost because of it.			E_1 E_2
4	The number of industrial robots has increased significantly since the 2000s.			E_3
5	The low operating costs of robots make them competitive with human workers.			E_3
6	In the finance sector, computer algorithms can execute stock trades much faster than a human, needing only a fraction of a second.			E_3
7	As these technologies become cheaper and more accessible, they will be implemented more widely, and humans might be increasingly replaced by AI.	C_3	+1	
8	According to Harvard Business Review, most operations groups adopting RPA have promised their employees that automation would not result in layoffs.	C_4	-1	E_4
9	AI is incredibly smart, but it will never match human creativity.	C_5	-1	

IAM Dataset - Statics Comparison

	Topics	Articles	Articles with claims	Claims	Support	Contest	Claims with evidence	Evidence	CEPs
Levy et al. (2014)	32	326	2	976	-		-	-	-
Rinott et al. (2015)	39	274	274	1,734	-	*	1,040	3,057	5,029*
Aharoni et al. (2014)	33 (12)	586	321 (104)	1,392	-	4	(350)	(1,291)	1,476*
Bar-Haim et al. (2017)	55	-	-	2,394	1,324	1,070	-	-	-
IAM (Ours)	123	1,010	814	4,890	2,613	2,277	3,302	9,384	10,635

Table 2: Overall statistics comparison of the existing datasets and our dataset. Note that: (1) in Aharoni et al. (2014)'s dataset, the numbers in the parenthesis refer to the evidence labeling data; (2) the numbers with * are calculated by us since they are not shown in the original papers.

Comprehensive & Large-Scale

Existing Tasks

- Task 1 Claim Extraction
- Task 2 Evidence extraction
- Task 3 Stance classification

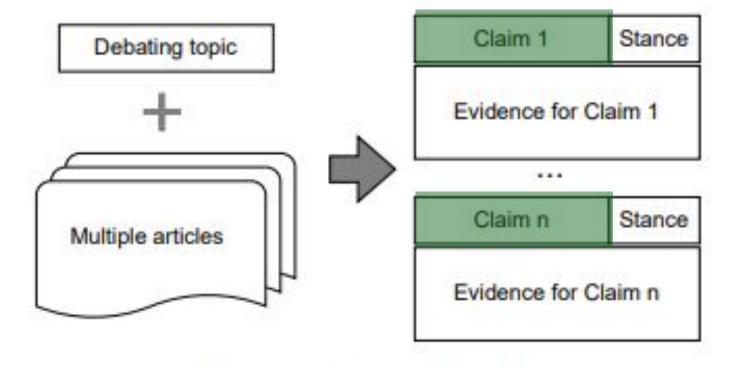


Figure 1: A flow chart showing the debating preparation process.

Existing Tasks

- Task 1 Claim Extraction
- Task 2 Stance classification
- Task 3 Evidence extraction

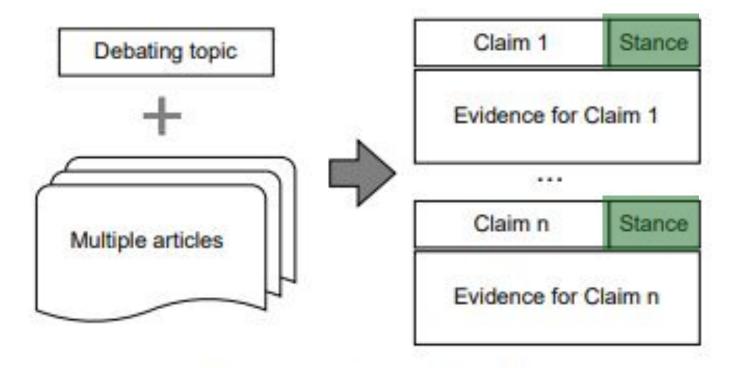


Figure 1: A flow chart showing the debating preparation process.

Existing Tasks

- Task 1 Claim Extraction
- Task 2 Stance classification
- Task 3 Evidence extraction

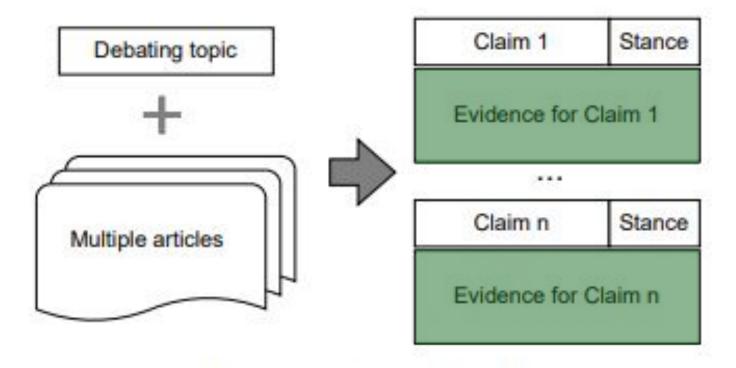
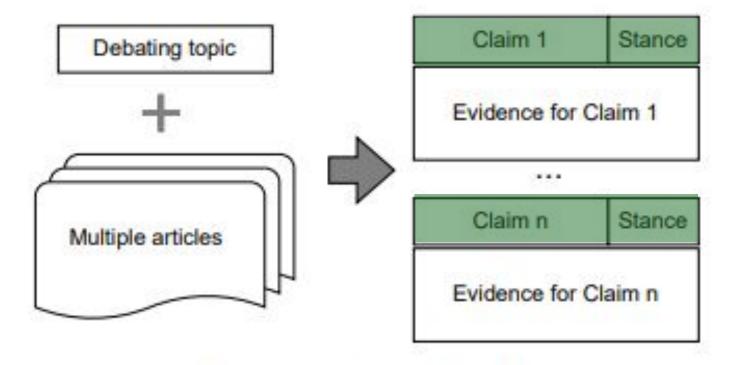


Figure 1: A flow chart showing the debating preparation process.

New Integrated Tasks

- Task 1 Claim Extraction
- Task 2 Stance classification
- Task 3 Evidence extraction



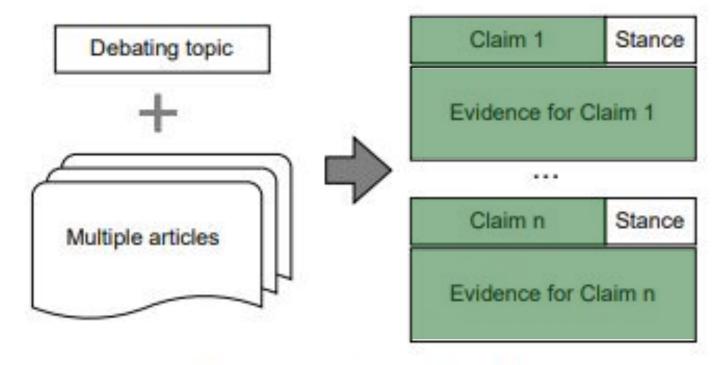
New integrated tasks:

Figure 1: A flow chart showing the debating preparation process.

- Task 4 Claim extraction with stance classification(CESC)
- Claim-evidence pair extraction (CEPE)

New Integrated Tasks

- Task 1 Claim Extraction
- Task 2 Stance classification
- Task 3 Evidence extraction



New integrated tasks:

Figure 1: A flow chart showing the debating preparation process.

- Task 4 Claim extraction with stance classification(CESC)
- Task 5 Claim–evidence pair extraction (CEPE)

Approaches

Existing tasks:

- Task 1 Claim Extraction
- Task 2 Stance

classification



Sentence pair

- Task 3 Evidence extraction New integrated tasks:
- Task 4 Claim extraction with stance classification(CES)



Pipeline: Task1 +



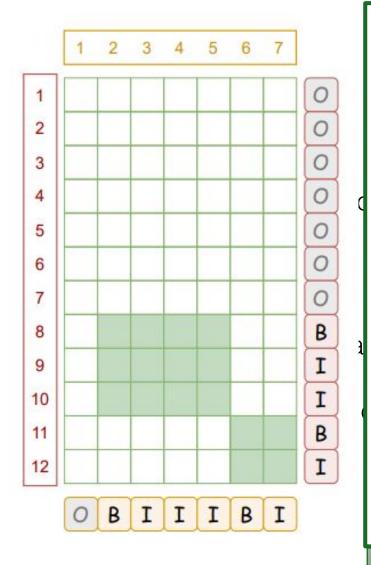
Multi-Label

Task 5 – Claim-evidence pair extraction (CEPE)



Pipeline: Task1 +

Multi-Task model (Cheng et al.



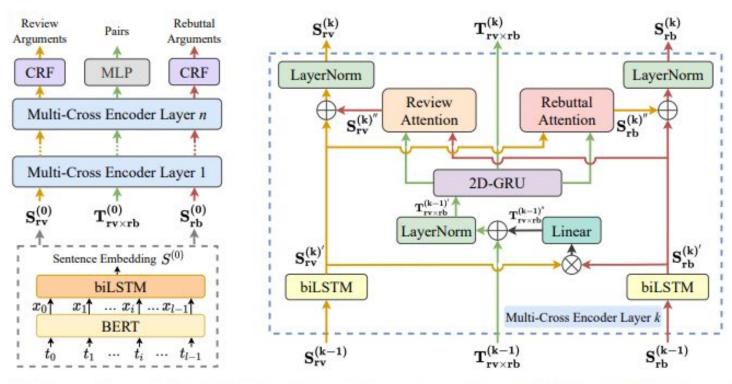


Figure 2: Overview of our model architecture with n multi-cross encoder layers (shown on the left). The sentence embedder (in the grey dotted box at the bottom left) shows the process of obtaining initial review and rebuttal sentence embeddings from pre-trained BERT token embeddings with biLSTM. The kth multi-cross encoder layer (in the blue dotted box on the right) shows the process of getting the sentence representations of review and rebuttal and the pair representations for the next layer.

the attention-guided multi-cross encoding-based

Task 5 - Claim-evidence Parl extraction (CEPE)



Multi-Task model (Cheng et al.

Experiments - Claim Extraction

Models	Macro F ₁	Micro F ₁	Claim F ₁
BERT-base-cased	72.08	92.51	48.08
RoBERTa-base	72.36	91.09	50.35

Table 5: Claim extraction performance.

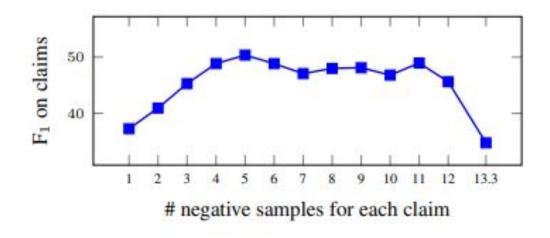


Figure 2: Effect of negative sampling for claim extraction with RoBERTa-base model.

Experiments – Stance Classification

Models	Acc.	Support F ₁	Contest F ₁
BERT-base-cased	73.43	73.08	73.78
RoBERTa-base	81.21	81.21	81.21

Table 6: Stance classification performance.

Experiments – Evidence Extraction

Models	Macro F ₁	Micro F ₁	Evi. F ₁
BERT-base-cased (T+C)	58.17	72.75	38.15
RoBERTa-base (T+C)	62.43	78.13	40.89
BERT-base-cased (C)	58.01	72.65	37.92
RoBERTa-base (C)	63.37	80.29	40.16

Table 7: Evidence extraction performance.

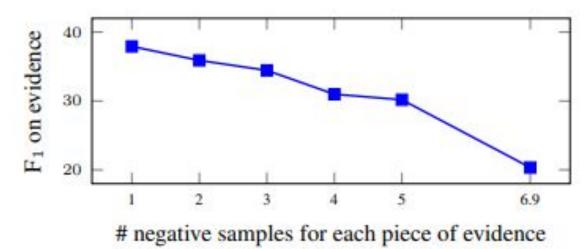


Figure 3: Effect of negative sampling for evidence extraction with BERT-base-cased (C).

Experiments — Claim Extraction with Stance Classification(CESE)

Models	Macro F ₁	Micro F ₁	Support F ₁	Contest F ₁
Pipeline	55.95	88.56	33.39	40.10
Multi-label	60.25	91.22	38.34	47.31

Table 8: CESC task performance.

Experiments - Claim-evidence pair extraction (CEPE)

Models	Precision	Recall	$\mathbf{F_1}$
Pipeline	16.58	22.11	18.95
Traversal	24.06	38.74	29.69
Multi-task	43.54	30.57	35.92

Table 9: CEPE task performance.

Conclusion

- Argument Mining Task들을 위한 데이터들을 통합하고 주석처리한 대규모 데이터셋 IAM 구축
- 실용적이고 효과적인 통합 Task인 CESC와 CEPE를 처음으로 제안
- 새로운 데이터셋으로 지금까지의 Argument mining task들에 대한 실험을 수행

Open question

• LLM을 활용해서 비슷하게 주석 처리된 Argument Mining 데이터셋을 만들 수 있을까?