Tsinghua University

DEEM: Dynamic Experienced Expert Modeling for Stance Detection

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Background

What is Stance Detection?

Stance detection is a natural language processing (NLP) task that automatically identifies the stance towards a specific target in a given text.

Text

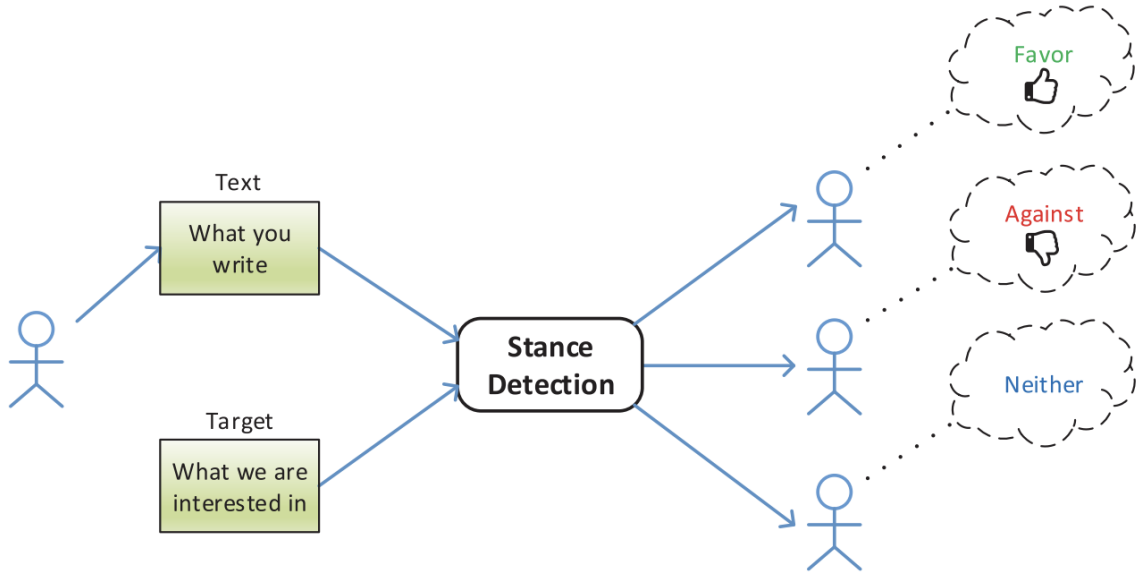
Are you actually trying, as president of the U.S., to start a war??!! #VoteBlueToSaveAmerica2020 #Biden

Target

Joe Biden

Stance

Favor, Against or Neither?



SemEval-2016 Task 6: Detecting Stance in Tweets (Mohammad et al., SemEval 2016)

Background

The Definition of Stance Detection?

Stance detection is a natural language processing (NLP) task that automatically identifies the stance towards a specific target in a given text.

Text

Are you actually trying, as president of the U.S., to start a war??!! #VoteBlueToSaveAmerica2020 #Biden

Target

Joe Biden

Stance

Favor, Against or Neither?

Social media

Short and Intricate

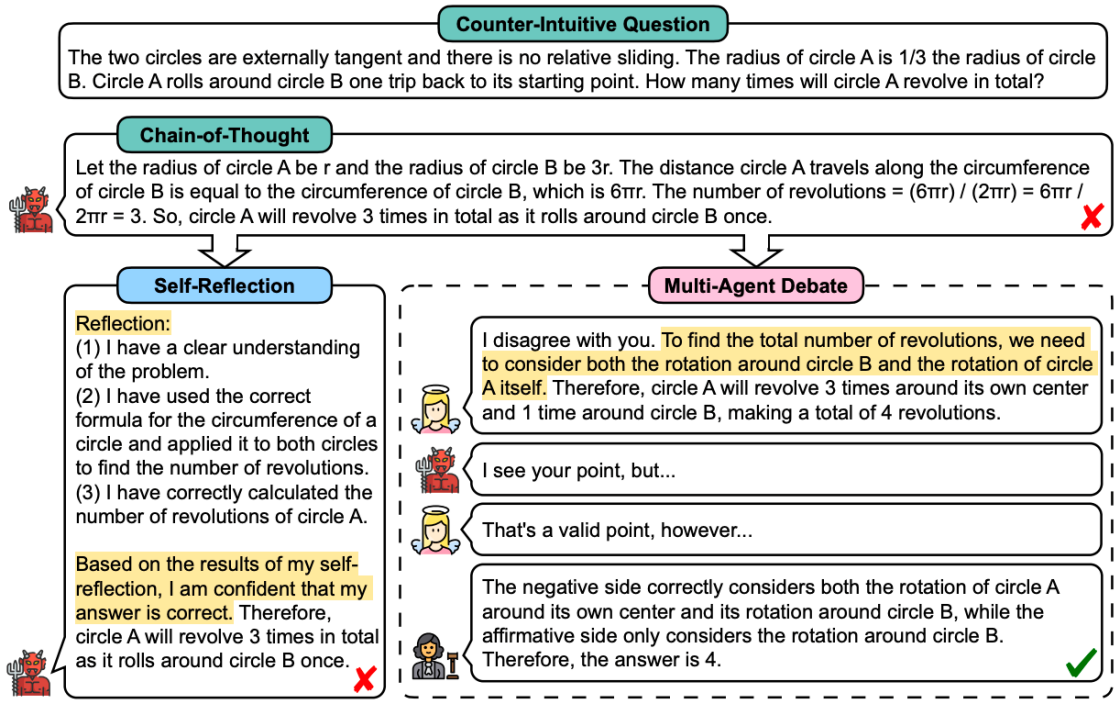
Additonal domain expertise

SemEval-2016 Task 6: Detecting Stance in Tweets (Mohammad et al., SemEval 2016)

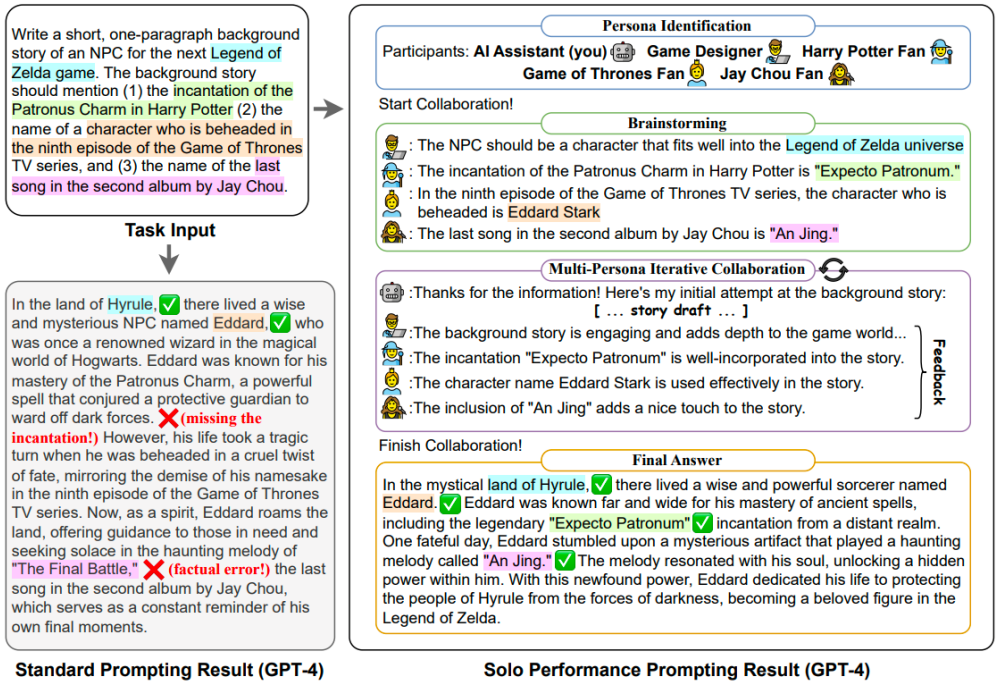
Previous Work

Wisdom of crowds

Liang et al., Wang et al., have attempted to solve reasoning tasks with multi-agent debate and multi-persona self-collaboration.



Liang etal Propose Multi-agents debate



Wang etal Propose Multi-agents collaboration

Previous Work

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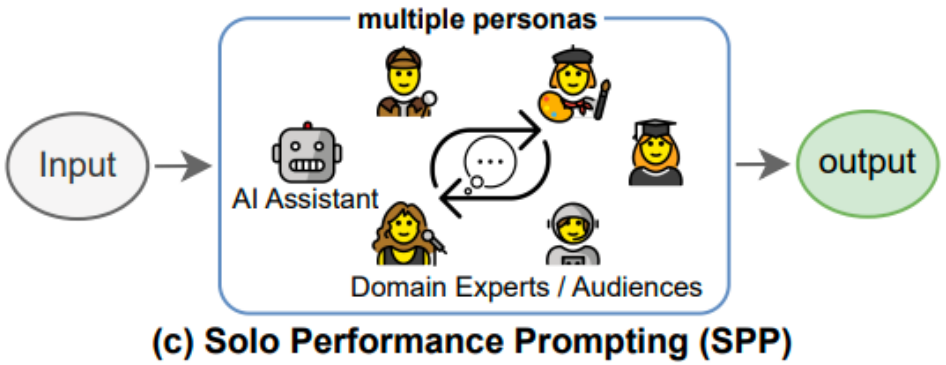

(c) Solo Performance Prompting (SPP)

@GovWhitmer @gretchenwhitmer \#WhenCoronaVirusIsOver \#bipartisanship .... You had better find a new job. \& I bet it is NOT AS A DOCTOR!!! \#Trump

Solo Performance Prompting

Medical_Expert: The author is suggesting GovernorWhitmer should not be a doctor, which could be seen as a derogatory comment towards the medical profession. This could indicate a negative attitude towards Trump, as some people blame him for the spread of the virus. ✗

However, their designed agents are generally pre-defined or automatically generated by LLMs, which either require strong prior knowledge or need to be further improved for stance detection tasks. Obviously, pre-defined agents are fixed, thus it is difficult to adapt to different contexts in social media. Moreover, **fully generated agents by LLMs may not be suitable due to the intricate contextualized information, especially in specific domains.**

Our Method

Method

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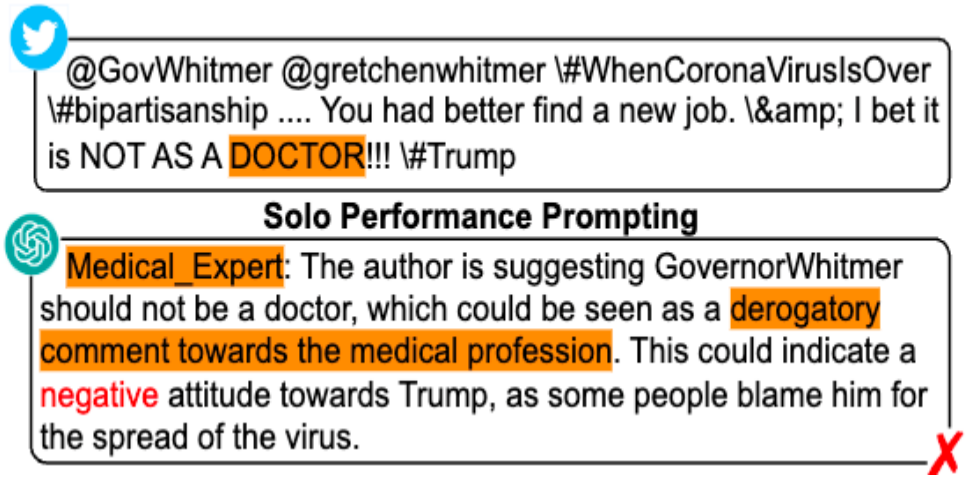
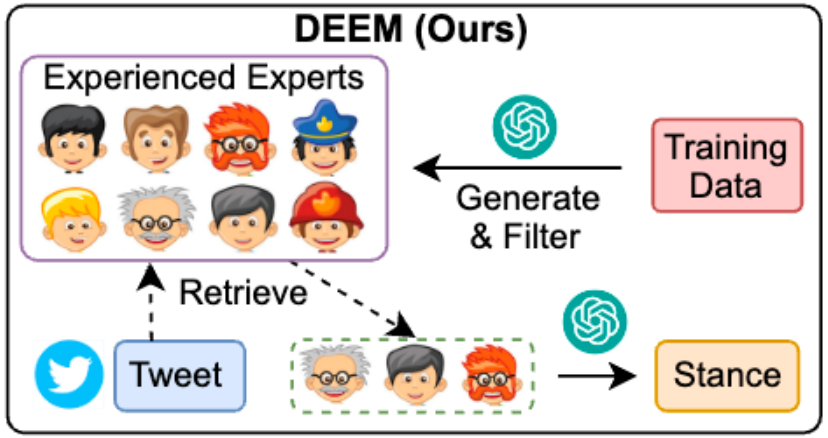
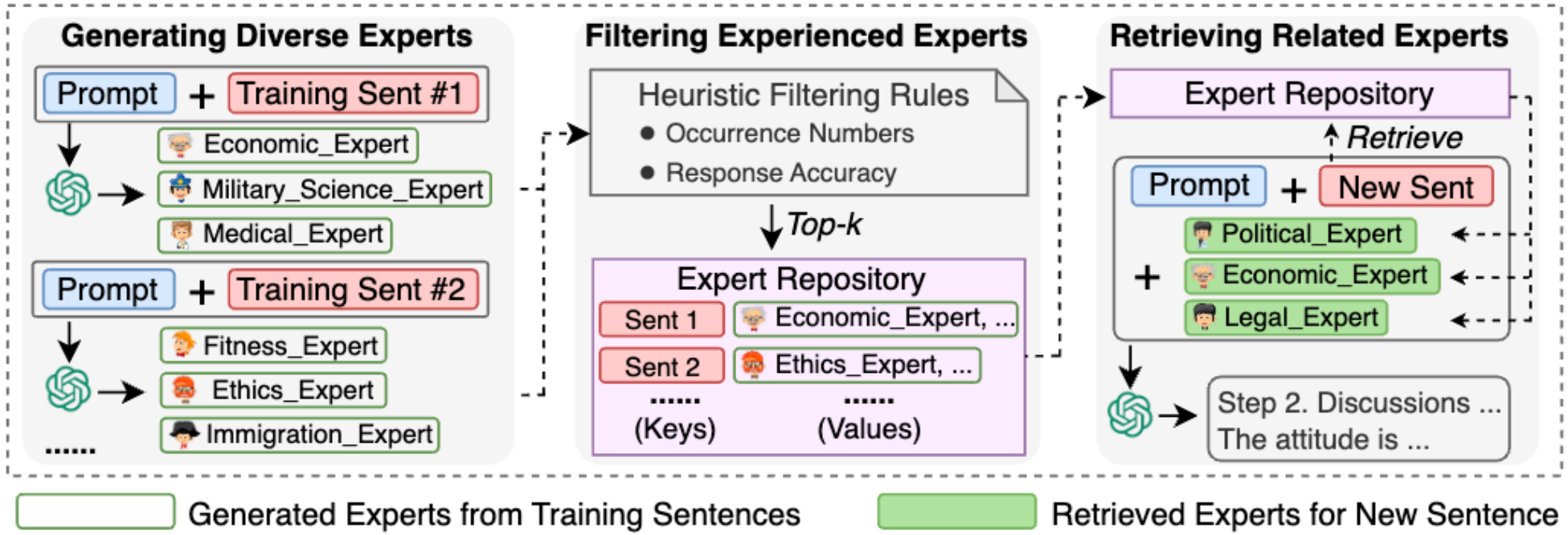




Method	Including Explanations	Multi-Roles	Verified Experts	Reasoning Type
Few-Shot	✗	✗	-	Gen
CoT	✓	✗	-	Gen
Auto-CoT	✓	✗	-	Re+Gen
ExpertPrompt	✓	✗	✗	Gen
SPP	✓	✓	✗	Gen
DEEM (ours)	✓	✓	✓	Re+Gen

Our Method

Method



@GovWhitmer @gretchenwhitmer \#WhenCoronaVirusIsOver \#bipartisanship .... You had better find a new job. \& I bet it is NOT AS A DOCTOR!!! \#Trump

Solo Performance Prompting

Medical_Expert: The author is suggesting GovernorWhitmer should not be a doctor, which could be seen as a derogatory comment towards the medical profession. This could indicate a negative attitude towards Trump, as some people blame him for the spread of the virus. ✗

DEEM

Political_Expert: The author is suggesting that she is not doing a good job in handling the coronavirus pandemic and she should find a new job. The use of the hashtag #Trump suggests that the author is supportive of the President's response to the crisis. ✓

Experiments

Datasets

Datasets	Target	Train	Test
P-Stance	Trump	6,362	796
	Biden	5,806	745
	Sanders	5,056	635
SemEval-2016	Clinton	1,898	984
	Trump	2,194	707
MTSD	Trump-Clinton	1,240	355
	Trump-Cruz	922	263
	Clinton-Sanders	957	272

Table 2: Statistics of P-Stance, SemEval-2016, and MTSD datasets.

Baseline

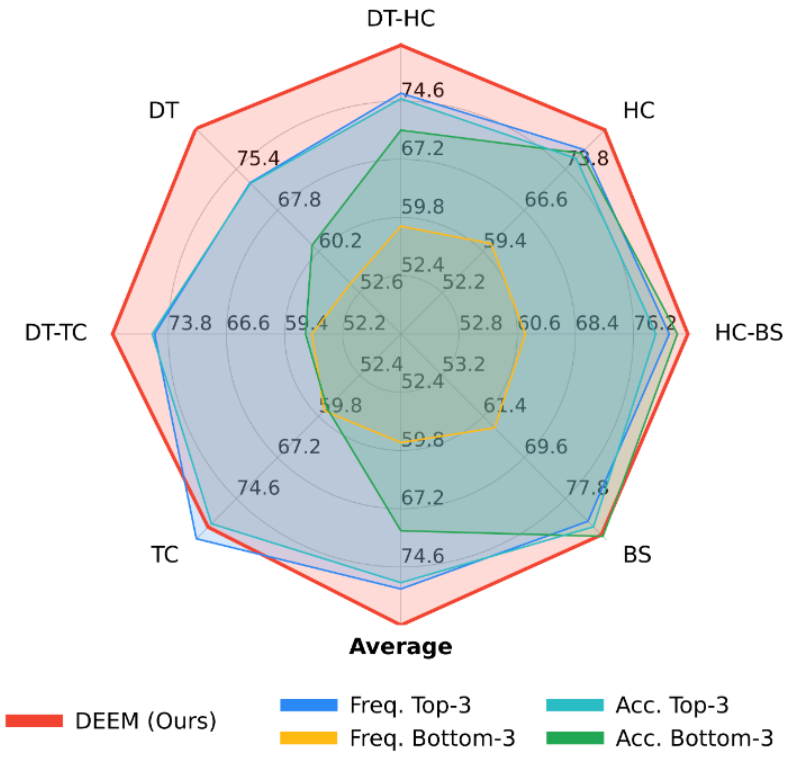
- Few-Shot
- Manual-CoT
- StSQA
- Auto-CoT
- ExpertPrompt
- SPP

Main Results

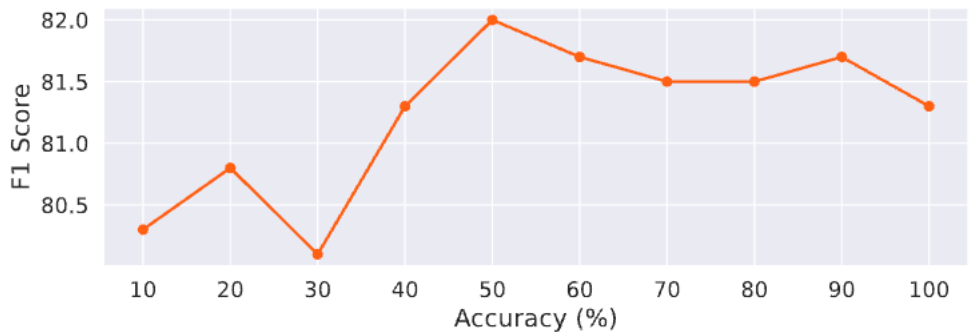
Type	Method	P-Stance			SemEval-2016		MTSD			Avg.
		DT	JB	BS	HC	DT	DT-HC	DT-TC	HC-BS	
FT	BiCond (Augenstein et al., 2016)♠	73.0	69.4	64.6	32.7†	30.5†	-	-	-	-
	BERT (Devlin et al., 2019)♠	81.6	81.7	78.4	49.6†	40.1†	-	-	-	-
	BERTweet (Nguyen et al., 2020)	82.4	81.0	78.1	50.9†	42.2†	69.2	70.7	69.0	67.9
	JointCL (Liang et al., 2022b)♡	-	-	-	54.8†	50.5†	-	-	-	-
	(text-davinci-003)									
ZS	Zero-Shot (Brown et al., 2020)	73.8	83.3	77.5	71.8	68.3	61.6	64.7	61.4	70.3
	DQA (Zhang et al., 2022)	73.0	80.8	76.1	72.7	69.9	58.9	66.4	63.3	70.1
FS ($d = 2$)	Few-Shot (Brown et al., 2020)	79.9	85.2	78.6	79.4	73.5	68.6	65.9	70.7	75.2
	Manual-CoT (Wei et al., 2022)	79.3	84.9	78.4	77.2	72.5	75.0	75.6	68.8	76.5
	StSQA (Zhang et al., 2023a)	75.2	85.2	78.9	78.3	72.3	72.6	75.9	72.0	76.3
	Auto-CoT (Zhang et al., 2023b)	82.9	84.7	78.4	80.7	73.8	67.9	67.4	75.3	76.4
	ExpertPrompt (Xu et al., 2023a)	82.8	85.5	78.7	85.2	73.0	74.1	76.8	71.5	78.5
	SPP (Wang et al., 2023d)	83.4	85.5	79.6	85.5	73.3	73.0	78.0	76.8	79.4
	DEEM (ours)	**83.7**	**86.0**	**80.4**	**85.7**	**74.8**	**76.5**	**80.1**	**81.3**	**81.1**
	Δ (compare w/ second-best results)	+0.3	+0.5	+0.8	+0.2	+1.0	+1.5	+2.1	+4.5	+1.7
	(gpt-3.5-turbo-0301)									
ZS	Zero-Shot (Brown et al., 2020)	83.3	82.5	79.4	79.3	71.4	73.5	67.0	73.6	76.3
	DQA (Zhang et al., 2022)♠	83.2	82.0	79.4	78.0	71.3	66.2	63.2	69.3	74.1
FS ($d = 2$)	Few-Shot (Brown et al., 2020)	83.6	83.1	80.8	79.3	71.6	76.6	78.2	72.8	78.3
	Manual-CoT (Wei et al., 2022)	85.4	83.8	80.9	79.5	71.2	77.0	77.5	76.7	79.0
	StSQA (Zhang et al., 2023a)♠	85.7	82.8	80.8	78.9	71.6	77.5	78.2	81.2	79.6
	Auto-CoT (Zhang et al., 2023b)	84.1	82.8	80.6	84.6	73.5	77.0	76.9	76.7	79.5
	ExpertPrompt (Xu et al., 2023a)	84.7	84.7	81.2	83.8	77.4	80.6	77.0	79.0	81.1
	SPP (Wang et al., 2023d)	85.1	84.6	81.5	85.3	79.5	79.5	79.8	79.8	81.9
	DEEM (ours)	**86.4**	**86.1**	**82.1**	**85.9**	**80.5**	**81.7**	**80.7**	**83.5**	**83.4**
	Δ (compare w/ second-best results)	+0.7	+1.4	+0.6	+0.6	+1.0	+1.1	+0.9	+2.3	+2.5

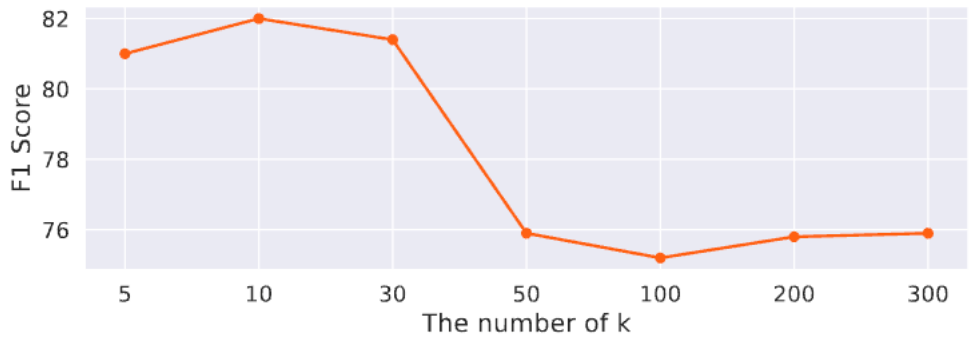
Analysis

- **Comparing with fixed experts**



- **Impact of filtering strategies accuracy (Top) and frequency (Bottom)**





Analysis

- Impact of (a) demonstrations, (b) retrieved experts, and (c) discussion turns during reasoning

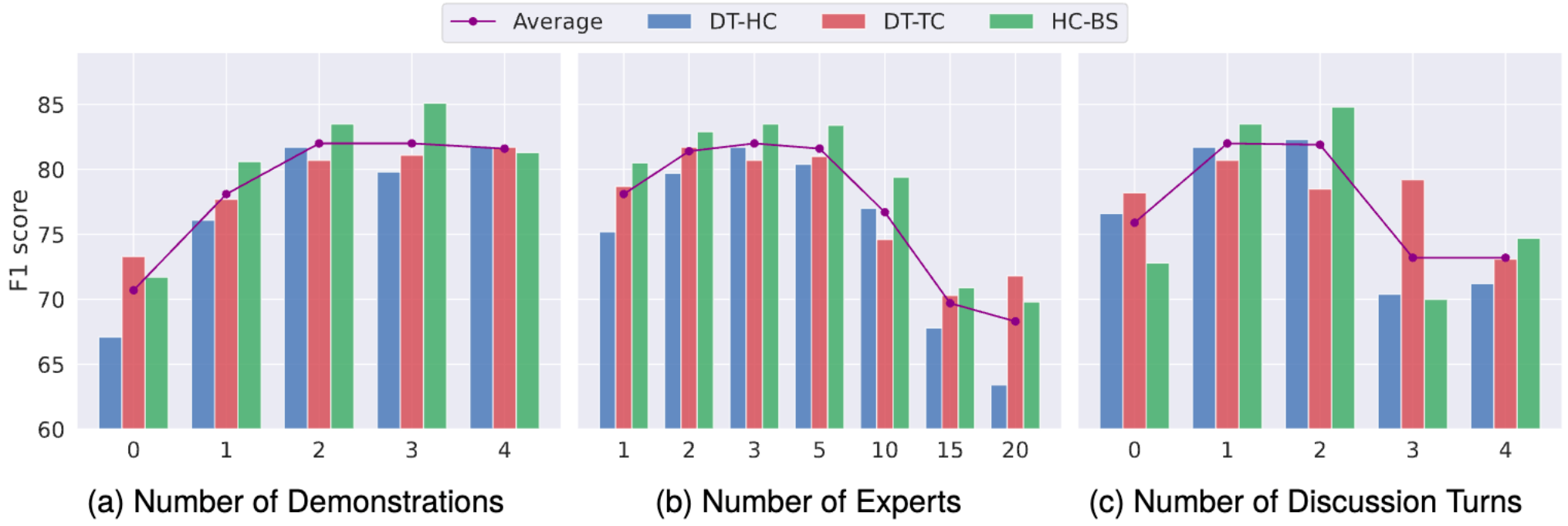


Figure 6: Impact of (a) demonstrations, (b) retrieved experts, and (c) discussion turns during reasoning.

Analysis

- To investigate the effect of “experts”, we compare self-consistency reasoning and two variants of our proposed DEEM.

Method	DT-HC	DT-TC	HC-BS
Few-Shot	76.6	78.2	72.8
Few-Shot + SC (N=3)	76.3	80.1	76.7
DEEM w/ “Person A/B/C”	77.2	79.0	77.0
DEEM w/ “Expert A/B/C”	78.6	78.7	76.7
DEEM (Ours)	**81.7**	**80.7**	**83.5**

Table 5: Results of few-shot reasoning, self-consistency (SC) reasoning, and variants of DEEM.

Method	Trump	Biden	Sanders	Avg.
BERTweet	47.6	53.6	53.6	51.6
DQA	43.9	45.7	45.2	44.9
StSQA	54.5	55.1	53.6	54.4
DEEM (Ours)	**60.9**	**64.8**	**67.6**	**64.4**

Table 6: Comparison between methods for the samples in P-Stance dataset with the label “neutral”.

Thanks!

Xiaolong Wang