Improving Consistency Identification in Task-oriented Dialogue Through Multi-Agent Collaboration

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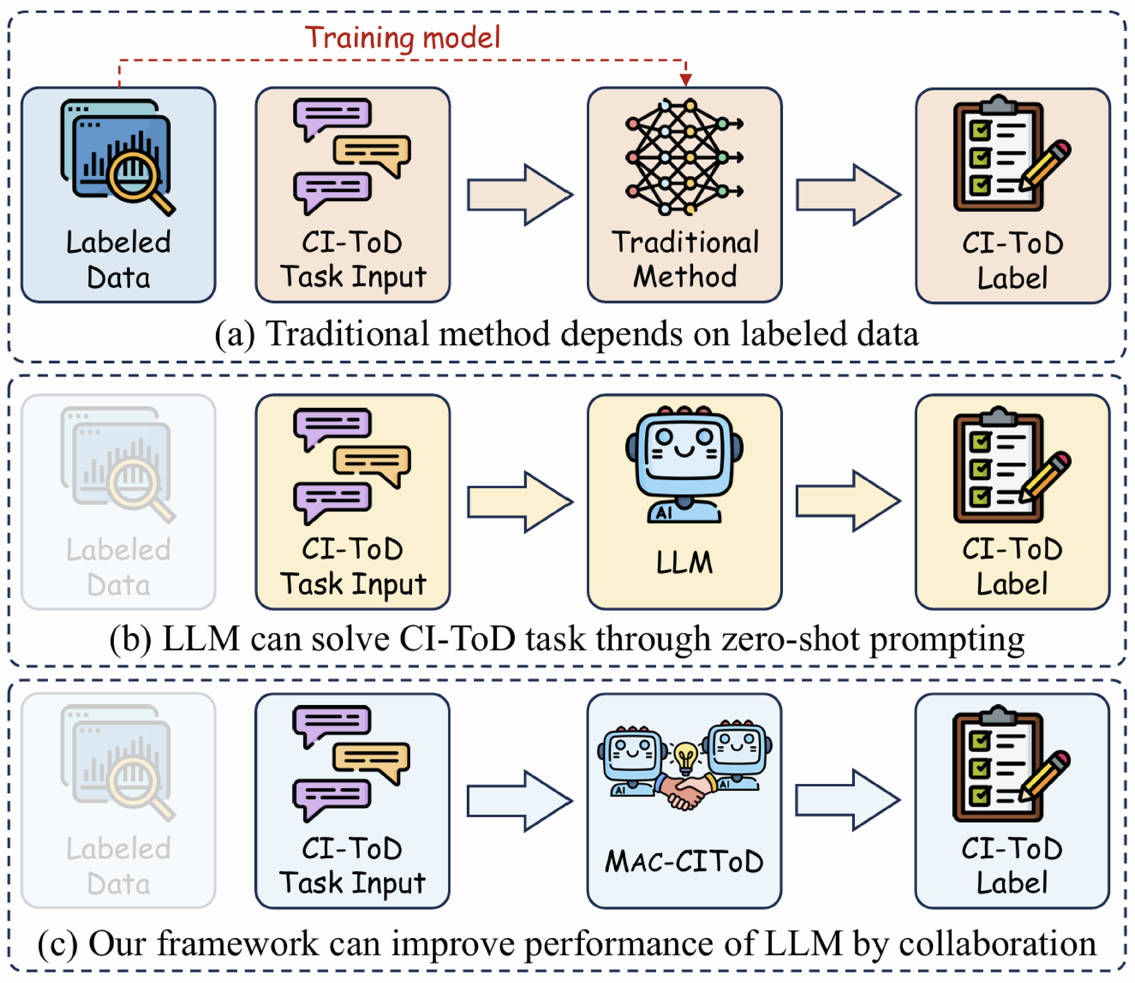
INTRODUCTION

- **Motvation**

  Current traditional approaches have achieved notable success in the Consistency Identification in Task-oriented Dialogue (CI-ToD) task; however, these methods ***depend heavily on high-quality labeled data*** (as illustrated in Figure (a)), which is often difficult to obtain in practical applications.

- **Our Contributions**
  - Large language models (LLMs) have garnered significant attention due to their impressive performance across various tasks. In this context, we ***firstly explore the application of LLMs*** in the CI-ToD task, as depicted in Figure (b).
  - Furthermore, to ***effectively model interactions across the related sub-tasks***: QI, HI, KBI, we propose a multi-agent collaboration framework ***MAC-CIToD***, illustrated in Figure (c).
  - Experiments on the standard benchmark demonstrate that the MAC-CIToD achieves superior performance, ***surpassing methods that require extensive training***.

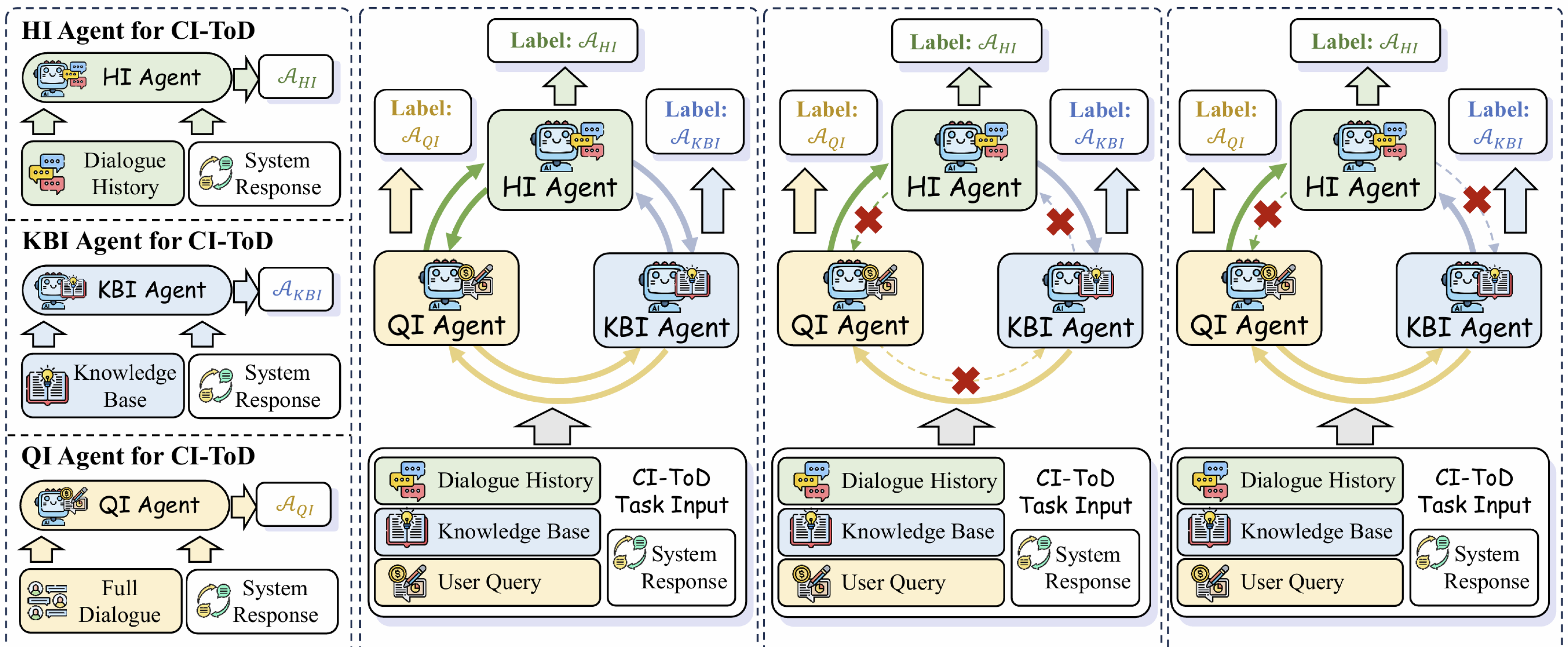


(a) Traditional method depends on labeled data

(b) LLM can solve CI-ToD task through zero-shot prompting

(c) Our framework can improve performance of LLM by collaboration

MAC-CIToD



(a) CI-ToD Basic Agents (b) MAC-CIToD (Full Connection) (c) MAC-CIToD (Cycle Connection) (d) MAC-CIToD (Central Connection)

The main framework of MAC-CIToD. Figure (a) presents the architecture of CI-ToD basic agents. Figure (b, c, d) presents the different multi-agent collaboration paradigms.

- ***CI-ToD Basic Agents (a)*** consist of three agents, each designed to model related sub-tasks and output initial answers.
- ***Collaboration Paradigms (b-d)*** based on the initial answers, we set up different collaboration paradigms in the following turns to model their contribution.
  - ***Full Connection (b)*** assists the agent by providing all labels from CI-ToD basic agents.
  - ***Cycle Connection (c)*** allows all neighboring agents to transmit labels in one direction of the cycle.
  - ***Central Connection (d)*** selects a central agent to receive all labels from the other agents.

EXPERIMENTS

- **Main Results**

Method	QI F1	HI F1	KBI F1	Overall Acc.
Traditional method†				
BERT-multi-task [Devlin *et al.*, 2019]	0.691	0.555	0.740	0.500
XLNet-multi-task [Yang, 2019]	0.725	0.487	0.736	0.509
Longformer-multi-task [Beltagy *et al.*, 2020]	0.717	0.500	0.710	0.497
BART-multi-task [Lewis *et al.*, 2020]	0.744	0.510	0.761	0.513
CGIM [Qin *et al.*, 2022]	0.764	0.567	0.772	0.563
PPA [Ding *et al.*, 2024]	0.772	0.624	0.781	0.592
Llama-3.1-8B-Instruct [Dubey *et al.*, 2024]				
Reflexion [Shinn *et al.*, 2024]	0.376	0.175	0.312	0.094
Debate [Liang *et al.*, 2023]	0.372	0.152	0.403	0.075
S^3 Agent [Wang *et al.*, 2024b]	0.693	0.350	0.591	0.213
MAC-CIToD (Full Connection)	0.706 (+0.013)	0.480 (+0.130)	0.619 (+0.028)	0.242 (+0.029)
MAC-CIToD (Cycle Connection)	0.727 (+0.034)	0.483 (+0.133)	**0.677 (+0.086)**	**0.301 (+0.088)**
MAC-CIToD (Central Connection)	**0.753 (+0.060)**	**0.500 (+0.150)**	0.586 (-0.005)	0.283 (+0.070)
gpt-3.5-turbo [OpenAI, 2022]				
Reflexion [Shinn *et al.*, 2024]	0.491	0.285	0.530	0.330
Debate [Liang *et al.*, 2023]	0.579	0.351	**0.626**	0.194
S^3 Agent [Wang *et al.*, 2024b]	0.328	0.165	0.332	0.191
MAC-CIToD (Full Connection)	**0.800 (+0.221)**	0.545 (+0.194)	0.513 (-0.113)	**0.418 (+0.088)**
MAC-CIToD (Cycle Connection)	0.748 (+0.169)	0.528 (+0.177)	0.573 (-0.053)	0.415 (+0.085)
MAC-CIToD (Central Connection)	0.756 (+0.177)	**0.597 (+0.246)**	0.537 (-0.089)	0.406 (+0.076)
GLM-4-9B-chat [GLM *et al.*, 2024]				
Reflexion [Shinn *et al.*, 2024]	0.734	0.357	0.588	0.342
Debate [Liang *et al.*, 2023]	0.633	0.360	0.668	0.230
S^3 Agent [Wang *et al.*, 2024b]	0.583	0.056	0.312	0.336
MAC-CIToD (Full Connection)	**0.804 (+0.070)**	0.366 (+0.006)	**0.697 (+0.029)**	0.427 (+0.085)
MAC-CIToD (Cycle Connection)	0.782 (+0.048)	0.467 (+0.107)	0.660 (-0.008)	**0.437 (+0.095)**
MAC-CIToD (Central Connection)	0.742 (+0.008)	**0.488 (+0.128)**	0.680 (+0.012)	0.408 (+0.066)
Gemma-2-9B-It [Team *et al.*, 2024]				
Reflexion [Shinn *et al.*, 2024]	0.410	0.304	0.384	0.201
Debate [Liang *et al.*, 2023]	0.481	0.207	0.448	0.198
S^3 Agent [Wang *et al.*, 2024b]	0.815	0.538	0.660	**0.522**
MAC-CIToD (Full Connection)	0.884 (+0.069)	**0.624 (+0.086)**	0.687 (+0.027)	0.474 (-0.048)
MAC-CIToD (Cycle Connection)	**0.902 (+0.087)**	0.621 (+0.083)	**0.688 (+0.028)**	0.474 (-0.048)
MAC-CIToD (Central Connection)	0.896 (+0.081)	0.468 (-0.070)	0.671 (+0.011)	0.333 (-0.189)
gpt-4o [Achiam *et al.*, 2023]				
Reflexion [Shinn *et al.*, 2024]	0.702	0.482	0.724	0.506
Debate [Liang *et al.*, 2023]	0.798	0.520	0.766	0.484
S^3 Agent [Wang *et al.*, 2024b]	0.700	0.254	0.670	0.455
MAC-CIToD (Full Connection)	0.886 (+0.088)	0.550 (+0.030)	0.835 (+0.069)	0.512 (+0.006)
MAC-CIToD (Cycle Connection)	**0.910 (+0.112)**	0.582 (+0.062)	**0.840 (+0.074)**	0.556 (+0.050)
MAC-CIToD (Central Connection)	0.904 (+0.106)	**0.629 (+0.109)**	0.831 (+0.065)	**0.584 (+0.078)**

- These agent methods ***still have a gap*** from the performance of traditional methods.
- Our framework ***attains the best performance*** and surpasses traditional method PPA.
- Our framework can still ***achieve competitive performance on smaller LLMs***.

- **Analysis**

Method	Overall Acc	
Llama-3.1-8B-Instruct		
CI-ToD Basic Agents	0.145	
MAC-CIToD (worst connection method)	0.242	↑0.097
MAC-CIToD (best connection method)	0.301	↑0.156
gpt-3.5-turbo		
CI-ToD Basic Agents	0.406	
MAC-CIToD (worst connection method)	0.406	↑0.000
MAC-CIToD (best connection method)	0.418	↑0.012
gpt-4o		
CI-ToD Basic Agents	0.484	
MAC-CIToD (worst connection method)	0.512	↑0.028
MAC-CIToD (best connection method)	0.584	↑0.100

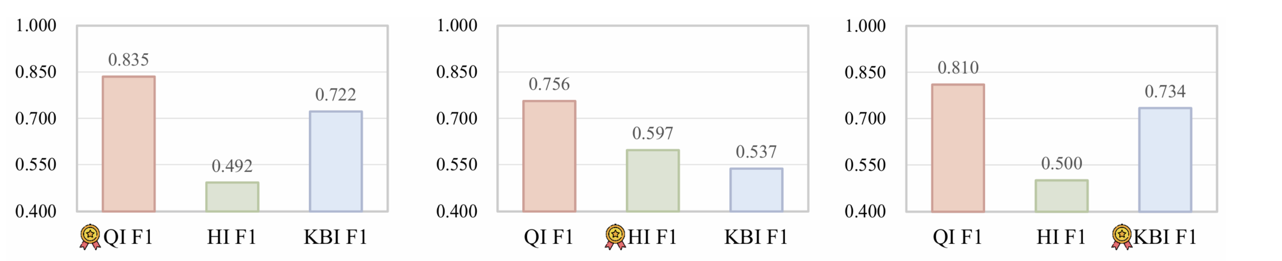
Table 2: The results of CI-ToD Basic Agents and MAC-CIToD. We selected the best and worst performance of MAC-CIToD for comparison based on overall Acc.

MAC-CIToD Remains Robust For All Connection Paradigms.

Input information	gpt-4o		GLM-4-9B-chat		gpt-3.5-turbo		Llama-3.1-8B-Instruct	
HI Agent	0.537		0.432		0.545		0.356	
+ QI Information	0.582	↑0.045	0.467	↑0.035	0.528	↓0.017	0.483	↑0.127
+ QI, KBI Information	**0.629**	↑0.092	**0.488**	↑0.056	**0.597**	↑0.052	**0.500**	↑0.144
+ QI, KBI, HI Information	0.550	↑0.013	0.366	↓0.066	0.545	↑0.000	0.480	↑0.124

Table 3: The performance of different input information. HI Agent presents the performance of HI F1 in CI-ToD Basic Agents. "+ Information" the performance of HI F1 in MAC-CIToD when inputting different information. **Bold number** presents the best results achieved by these input information on the current model.

Information From Different Sub-tasks Can Effectively Boost The Performance of The Target Sub-task.



(a) QI Agent as the central agent (b) HI Agent as the central agent (c) KBI Agent as the central agent

Figure 4: The results of different central agents in MAC-CIToD (Central Connection). This figure illustrates the F1 performance of MAC-CIToD (Central Connection) while QI Agent (a), HI Agent (b), and KBI Agent (c) as the central agent. The reward sign on the left side of F1 indicates that the performance of this central agent is the best when compared to other agents serving as the central agent.

The Performance of The Central Agent is Consistently The Best in MAC-CIToD Central Connection.

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