

Beyond Isolation: Multi-Agent Synergy for Improving Knowledge Graph Construction

Hongbin Ye
Zhejiang Lab
Zhejiang, China
yehongbin@zhejianglab.com

Honghao Gui
Ant Group
Zhejiang, China
guihonghao.ghh@antgroup.com

Aijia Zhang
Zhejiang Lab
Zhejiang, China
zhangaijia@zhejianglab.com

Tong Liu
Zhejiang Lab
Zhejiang, China
liutong@zhejianglab.com

Wei Hua
Zhejiang Lab
Zhejiang, China
huawei@zhejianglab.com

Weiqiang Jia
Zhejiang Lab
Zhejiang, China
jiaweiqiang@zhejianglab.com

ABSTRACT

Knowledge graph construction (KGC) is a multifaceted undertaking involving the extraction of entities, relations, and events. Traditionally, large language models (LLMs) have been viewed as solitary task-solving agents in this complex landscape. However, this paper challenges this paradigm by introducing a novel framework, CooperKGC. Departing from the conventional approach, CooperKGC establishes a collaborative processing network, assembling a KGC collaboration team capable of concurrently addressing entity, relation, and event extraction tasks. Our experiments unequivocally demonstrate that fostering collaboration and information interaction among diverse agents within CooperKGC yields superior results compared to individual cognitive processes operating in isolation. Importantly, our findings reveal that the collaboration facilitated by CooperKGC enhances knowledge selection, correction, and aggregation capabilities across multiple rounds of interactions¹.

CCS CONCEPTS

• **Computing methodologies** → **Information extraction; Cooperation and coordination.**

KEYWORDS

Knowledge Graph Construction, Information Extraction, Multi-agent Collaboration

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¹All code are available at <https://github.com/hongbinye/CooperKGC>.

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1 INTRODUCTION

In the era of information abundance, constructing comprehensive knowledge graphs [36, 54, 69] has emerged as a pivotal task, facilitating the organization and retrieval of structured information essential for various applications [1, 15, 50]. Prior research [30, 31, 40] in the domain has predominantly focused on fine-tuning task-specific models through extensive datasets, wielding the power of supervised learning. The advent of LLMs, such as GPT-3 [2] and ChatGLM [7], has revolutionized natural language processing by showcasing unparalleled proficiency in understanding and generating human-like text. However, the application of these models to KGC remains an intricate challenge, as this task necessitates not only language understanding but also precise extraction of elements within the confines of predefined schemas. Recent investigations [10, 22, 74] have revealed that, despite their triumphs in various natural language tasks, LLMs still grapple with performance shortcomings when confronted with the intricate demands of KGC tasks. Notably, Wei et al. [62] reveals that the raw textual data utilized to train large language models may lack task-specific schemas, resulting in a weakened semantic grasp and structural analysis of the underlying schema. Therefore we contend that a shift from traditional parameter-based paradigms to a more nuanced approach, like *Chain-of-Thought* (CoT) [61, 70], can address the challenges posed by multi-step inference problems inherent in KGC. By decomposing the information extraction task into distinct stages, it not only reduces search space but also computational complexity, thereby offering a promising avenue for improving KGC.

Embracing the profound insights from the *Society of Mind* (SOM) [35], which conceptualizes the mind as a complex system emerging from the interactions of simple components, our research explores the transformative potential of LLM-based agents in multi-agent systems. These agents [65] exhibit cooperative behaviors in diverse scenarios, spanning role-playing environments [21], the formation of interactive artificial societies [41], and task-oriented social simulations [26]. Taking inspiration from pioneering work of Liang et al. [27], we employ the multi-agent debate framework for collaborative self-reflection on challenging tasks. Collaboration is defined as an iterative refinement process, wherein each round generates a new answer based on prior answers and self-reflection. This iterative feedback fosters continuous improvement, making our collaborative approach adept at tackling problems that elude single-agent

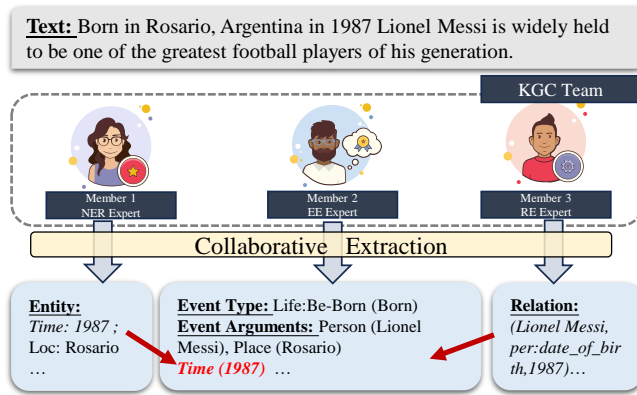


Figure 1: A knowledge graph construction team which consists of experts proficient in various tasks. In contrast to the previous stage decomposition methods, we construct it as a multi-intelligence collaborative process, which facilitates interaction based on collaborative mindset while introducing other perspectives.

solutions. Through this synergistic collaboration, the agent network transcends individual capabilities, paving the way for KGC.

Specifically, our dedicated team of agents comprises experts proficient in various tasks, including named entity recognition, relation extraction, and event extraction. Figure 1 illustrates a scenario where given a sentence "Born in Rosario, Argentina in 1987 Lionel Messi is widely held to be one of the greatest football players of his generation." Despite the event extraction agent successfully identifies the "Life:Be-Born" event triggered by the word "Born" and recognizes associated arguments "Lionel Messi" and "Rosario" with roles "Person" and "Place," respectively, it misses the crucial meta role "Time" for the argument "1987". Notably, the named entity recognition agent identifies "1987" as a time entity, while the relation extraction agent establishes the triplet "Lionel Messi, per:date_of_birth,1987". Through collaborative interactions within the team, the event extraction agent adeptly supplements the missing event arguments. This collaborative approach, inspired by the harmonious interaction [48] advocated by the SoM framework and akin to the dynamics of individuals [63] with different specialties in human society [46], demonstrates the advantages of multi-agent collaboration [34, 64]. In our approach **CooperKGC**, we construct a collaborative team of agents, each specializing in distinct tasks to simulate the nuanced teamwork prevalent in human society. The integration of open interaction, expertise refinement, and adaptability to others' opinions mirrors the foundations of a cohesive society. Our exploration into diverse collaboration strategies reveals key insights: (1) Inclusion of agents with varied expertise enhances collaboration outcomes. (2) While model hallucinations [68] may arise, effective communication among team members mitigates these drawbacks. (3) Substantial team collaboration enhances extraction results on target tasks; however, an intriguing observation emerges that increasing cooperation rounds doesn't invariably yield superior results. In our collaborative mechanism, balancing interaction frequency ensures the expert agent's beliefs

remain undisturbed by excessive external authoritative information, aligning with fundamental theories of sociology [8, 11, 53]. In summary, our work contributes the following:

- We introduce a pioneering method, **cooperKGC**, that capitalizes on the inherent reasoning capabilities of LLMs and orchestrates a multi-agent collaborative process to elevate the precision of existing models. Our empirical findings underscore the efficacy of this approach.
- We delve into the mechanics of collaboration within multi-agent teams. Our objective is to discern the nuances of team intelligence exhibited by LLMs possessing diverse expertise when engaged in collaborative endeavors. Enriching our study, we draw upon sociological theory to contextualize the behavioral and decision-making tendencies of expert agents within multi-turn conversational interactions.
- Intriguingly, our simulations, mirroring the subtle collaborative capabilities inherent in human society through LLM agents, unveil the significance of configuring adept team members and adopting efficient collaboration strategies for multi-agent systems. This revelation hints at a future where artificial intelligence becomes inherently collaboration-aware, marking a pivotal stride in the evolution of AI.

2 RELATED WORK

2.1 LLM-based Knowledge Graph Construction

Knowledge graph construction has evolved significantly from its early dependence on supervised learning methods. Recent years have witnessed a surge of interest in leveraging the remarkable advancements achieved by LLMs within the realm of KG. Notably, Zhu et al. [74] delves into the application of LLMs in KG construction and reasoning tasks, uncovering their commendable prowess in tasks such as reasoning and question answering. Building on this foundation, Zhang et al. [72] extends the exploration by integrating KG structural information into LLMs, employing self-supervised structural embedding pre-training to imbue models with structural awareness. Wei et al. [62], in a novel perspective, posits that LLMs inherently possess the capability for unified zero-shot information extraction in interactive settings. This belief led to the proposal of a two-stage framework that transforms information extraction into a multi-turn question and answer architecture. Furthermore, Pang et al. [39] pinpoints the unspecified task description as a key factor hindering the performance of contextual information extraction. To address this, a guided learning framework is introduced to enhance the extraction model's alignment with specified guidelines. In the broader landscape of NLP, diverse approaches have been explored to enhance reasoning in language models, ranging from scratchpad [37], verification [3], CoT [17, 44, 61], self-reflection [33, 47], and fine-tuning [20, 43, 71]. Techniques such as RLHF [28, 75], knowledge retrieval enhancement [12], and likelihood estimation-based training-free methods [16] have also been employed to bolster the factual consistency. Departing from the conventional isolation of KGC as a singular task, our approach advocates a departure from such isolation by fostering collaboration among a group of expert model agents in a multi-round social environment. This novel perspective encourages models to reflect on their solutions based on

	Has multiple agents involved?	Has personalized agents?	Has interactive rounds?	Involves chain of thought processes?	Accomplishes multiple tasks in parallel?
AutoKG [74]	✗	✗	✗	✗	✗
ChatIE [62]	✓ (2-agents)	✗	✓ (2-rounds)	✗	✗
GPT-NER [57]	✗	✓	✓ (>3-rounds)	✓	✗
GPT-RE [56]	✗	✓	✗	✓	✗
CoT-ER [32]	✓ (3-agents)	✗	✓ (3-rounds)	✓	✗
LM vs LM [4]	✓ (2-agents)	✓	✓ (3-stages)	✓	✗
Multiagent Debate [6]	✓ (2-agents)	✗	✓ (3-stages)	✓	✗
MAD [27]	✓ (3-agents)	✓	✓ (3-stages)	✓	✗
PRD [23]	✓ (2-agents)	✓	✓ (3-stages)	✓	✗
SPP [59]	✓ (>3-agents)	✓	✓ (4-stages)	✓	✗
Our CooperKGC	✓ (3-agents)	✓	✓ (3-stages)	✓	✓ (3-tasks)

Table 1: Comparison with previous methods. The upper half represents LLM-based KGC method, while the lower half showcases the emerging multi-agent approach applied to other tasks. Our CooperKGC pioneers a multi-expert collaborative processing method explicitly tailored for KGC tasks. Notable components include the ">3-rounds" concept, indicating iterative interactions beyond three rounds, the "3-stage" process involving statement, interactive debate, and summary iterations, and the more advanced "4-stage" introducing dynamic allocation of expert agents.

the outcomes of tasks performed by other agents, thereby ushering in a paradigm shift towards multi-agent synergy for KGC.

2.2 Interactive Collaboration of Multiple Agents

In the landscape of collaborative efforts among language model agents, a trend has emerged in recent years showcasing the robust performance achieved through the synergy of multiple agents across various tasks, offering a promising avenue to augment the capabilities of individual LLMs. Noteworthy advancements in facilitating collaboration among multiple agents include the development of diverse interaction architectures, often assigning agents to static roles. For instance, Du et al. [6] employs a two-model agent setup engaging in multiple rounds of debate, resulting in heightened factuality and reasoning capabilities, albeit at the cost of increased computational expenses. Similarly, Cohen et al. [4] introduces an examiner LLM to validate claims produced by the original LLM, leveraging a distinct division of labor to uncover factual errors. Hao et al. [13]’s contribution lies in the ChatLLM network, enabling dialogue-based language models to interact, share feedback, and collectively deliberate on problems, fostering diverse perspectives within the system. Furthermore, introducing a judge into the decision-making process, responsible for summarizing debates and rendering final conclusions [27, 66], demonstrates the potential of guided debates to enhance performance. To Address self-enhancement bias, Li et al. [23] proposes a framework incorporating peer review and discussion. While Wang et al. [59] explores the role of multiple agents in rounds of self-collaboration, concentrating on refining problem-solving capabilities for a singular complex task. In this study, we inherit previous methods by presenting an interactive architecture tailored for a knowledge graph construction team comprising agents with distinct expert skills. A departure from prior work, our innovation lies in introducing the challenge of completing multiple information extractions, aligning with the principles of feedback compatibility.

3 PRELIMINARIES

In this paper, we apply our approach, **cooperKGC**, to three representative tasks of knowledge graph construction, namely: Named Entity Recognition (NER), Relation Extraction (RE) and Event Extraction (EE). Notably, since these three tasks are relevant in some way, we leave the exploration of cross-domain collaboration for future work. We provide definitions for these sub-tasks and then explain the basic structure of current models.

3.1 Task Definition

Named Entity Recognition. Standing as a fundamental and pivotal undertaking in the construction of knowledge graphs, this task involves the identification of entities within texts and their subsequent classification into predefined categories, encompassing names of individuals, geographical locations, proper nouns, organizational designations, etc. A prime example illustrating the significance of NER is evident in the sentence “Messi wins record-extending 8th Ballon d’Or in 2023.”. In this context, the model is tasked with pinpointing the specific entities representing *Person* (Messi) and *Time* (2023). The proficiency of NER in discerning such elements is instrumental in extracting meaningful information from textual data and facilitating the organization of KGs.

Relation Extraction. The crucial task of knowledge graph construction involves simultaneously extracting entity mentions and their relations, represented as triples (subject, relation, object), from unstructured texts. Given the input sentences, the desired outputs are relational triples (e_h, r, e_t) , where e_h is the head entity, r is the relation, and e_t is the tail entity. For instance, given the sentence “Kylian Mbappé grew up in Bondy, one of the Parisian suburbs with working-class, mostly immigrant residents.”, the model should identify two entities *Kylian Mbappé* and *Bondy*, together with their relation *person-place-lived*, described as triple (*Kylian Mbappé*, *person-place-lived*, *Bondy*).

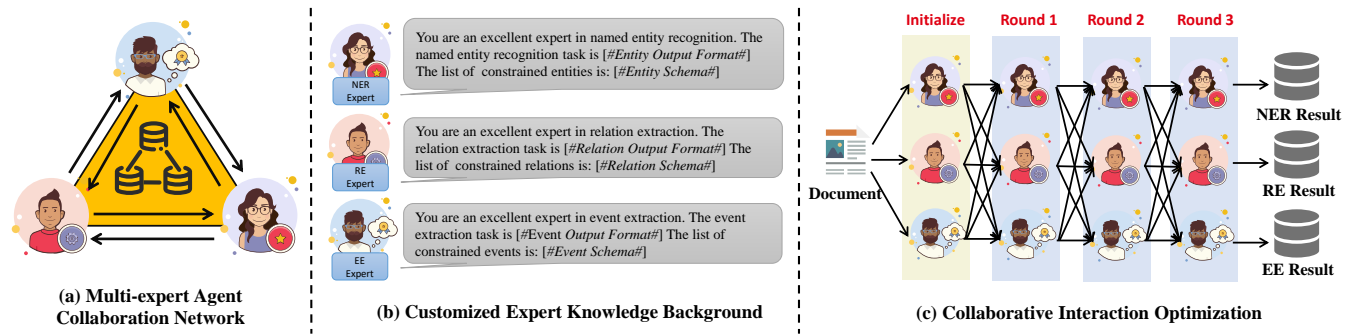


Figure 2: The overview of our CooperKGC.

Event Extraction: The automated extraction of events from unstructured natural language texts, guided by an event schema, constitutes event extraction. To elaborate on the procedure, terms are defined as follows: a trigger word denotes a word or phrase that best characterizes the event, while an event argument represents an entity or attribute associated with the event, such as the place or time. For example, the sentence “Li Shaomin was convicted of espionage and deported.” describes an *Convict* event triggered by the word ‘convicted’. This event includes two argument roles: the *Defendant* (Li Shaomin) and the *Crime* (espionage). The model should be able to identify event triggers, their types, arguments, and their corresponding roles.

3.2 Problem Formulation

In the context of an original text X , the objective is to extract the requisite elements $\mathcal{Y} = \{\mathcal{Y}^1, \dots, \mathcal{Y}^n\}$, in alignment with the pre-defined constraints outlined by the schema S . Note that $\mathcal{Y}^i, i \in t$ represents the information to extract for the i -th type, and n refer to the number of types. For the named entity recognition task, \mathcal{Y}^i is in the form of tuples $\mathcal{Y}^i = (\text{entity} - \text{type}, \text{entity} - \text{span})$. For the relation extraction task, \mathcal{Y}^i is in the form of triples $\mathcal{Y}^i = (e_h, r, e_t)$, including the head entity, tail entity, and corresponding relation. For the event extraction, \mathcal{Y}^i contains the event record in the sentence, which can be represented as $\mathcal{Y}^i = \{\text{event} - \text{type}, \text{event} - \text{trigger}, \text{argument} - \text{span}, \text{argument} - \text{role}\}$. In the following sections, we present the details of team formation and interaction.

4 METHODOLOGY

Illustrated in Figure 1, we introduces a collaborative framework COOPERKGC, aimed at advancing knowledge graph construction by concurrently extracting component elements such as entities, relations, and events. This framework promotes the interconnection of agents engaged in various tasks through collaborative team efforts (Section 4.1). Building upon this collaborative foundation, we delve into the customization of expert knowledge backgrounds for each agent (Section 4.2). A strategic approach is introduced to multiple rounds of collaborative interaction, aimed at refining individual extraction results by comprehensively incorporating the perspectives of other agents (Section 4.3). Notably, our method could extend beyond the confines of the selected three tasks, offering flexibility through a dynamically formulated team collaboration

network tailored to specific task requirements. This adaptive and collaborative approach underscores our commitment to moving “Beyond Isolation,” fostering multi-agent synergy for an improved and nuanced KGC process.

4.1 Construction of Multi-expert Agent Collaboration Network

In the collaboration process of LLM-agents, our approach advocates a dynamic exchange of text messages through multiple rounds of interactions. Traditional methods often treat expert agents, each equipped with distinct back-ends, as isolated nodes within the collaborative network. These nodes independently contribute to task-solving through separate thinking chains, and a central adjudication node amalgamates and rectifies their responses. However, this conventional solution reveals two critical flaws: (1) The adjudication node, functioning as the central hub, exhibits low fault tolerance and demands substantial reasoning ability to assimilate opinions from nodes spread across diverse collaborative networks. This centralized load imposes elevated requirements on the system; (2) The team heavily relies on the ruling node as the sole consensus mechanism, hindering effective interactions between participants in the KGC task.

In response to these limitations, we advocate a decentralized collaborative network communication scheme. Here, each expert agent backend, responsible for handling a specific task, establishes a bidirectional communication channel with any other expert agent backend. Despite the asynchronous nature of message production during practical operations, we adopt rounds as the fundamental unit of interaction to accomplish designated tasks and facilitate replica communication among expert agents. It is noteworthy that, although our approach draws inspiration from the Byzantine Fault Tolerance [18] to form a distributed network, the message records held by each agent node differ. This divergence arises due to the inherent constraints of LLMs related to token length and reasoning performance bottlenecks. In the process of replica communication, we implement message simplification, whereby extraction results complying with schema constraints are distilled. This strategic simplification enhances the efficiency of information exchange and ensures a more seamless and organized collaborative effort in the construction of knowledge graphs. The formalization of the abstract collaboration network comprises three fundamental components:

Expert Nodes. Expert nodes embody agents proficient in specific sub-tasks within KGC. They assimilate context from their peers at the preceding time step and formulate responses based on the input text \mathcal{X} . Notably, an Expert node can take various forms, including a vanilla LLM guided by explicit instructions, a self-reflective agent with a chain of thinking, or an agent explicitly leveraging domain knowledge through external knowledge bases or tool libraries. With this foundation, our focus shifts to the collaborative functions between agents. Formally, the response r_i^t of the i -th agent at the t -th round is expressed as a function \mathcal{F}_t^i , mapping from the base input text \mathcal{X} , prompt p_i^t , and predecessor expert agent's replicas \mathcal{R}_{t-1} : $r_i^t = \mathcal{F}_t^i(\mathcal{X}, p_i^t, \mathcal{R}_{t-1})$, where $\mathcal{R}_{t-1} = \{r_{t-1,j} | j = 1, 2, \dots\}$. Let \mathcal{A} be the set of all expert nodes and T be the maximum round.

Communication Edges. A two-way communication channel facilitates the exchange of insights among expert nodes \mathcal{A} in the KGC collaboration network. In this context, we define \mathcal{E} as the set encompassing all edges within the system. Recognizing the nuanced distinctions in information dissemination, we establish directional edges, represented by $e_{m,n} = (a_{t-1}^m, a_t^n) \in \mathcal{E}$, where a_{t-1}^m and a_t^n signify the adjacent agent responsible for transmitting replica. It was, a_t^n can perceive the replica passed from a_{t-1}^m as its contextual input. Thus, the expert nodes are intricately linked through these communication edges, constituting the interactive communication units $\mathcal{C} = (\mathcal{A}, \mathcal{E})$.

Replicas Delivery. In the interactive communication unit \mathcal{C} , replica delivery serves as the conduit guiding the flow of information from an agent in $(t-1)$ -th round to the input message queue of another agent in t -th round. To streamline this intricate exchange, we designate a specific simplification function \mathcal{S} to simple the information: $d_{t-1} = \mathcal{S}(r_{t-1})$, where \mathcal{S} predigest the complex CoT reasoning process. Therefore, the replicas queue collected by the i -th expert node is expressed as $\mathcal{D}^i = \{d_{t-1}^j | j \neq i\}$.

4.2 Customized Expert Knowledge Background.

In order to unleash the ability of different expert agents to collaborate on complex extraction problems, we introduce customized expert knowledge background. This context comprises three key components: (1) Opening statement \mathcal{P}_o , where each expert agents is presented with a directive elucidating how it can contribute its unique expertise to address a KGC task; (2) Task definition \mathcal{P}_t , which outlines the specifics of the knowledge graph extraction, including the targeted elements and the guiding schema; and (3) In-context demonstration \mathcal{P}_c , involving the selection of a limited set of M instances. The overarching objective of this in-context demonstration is to furnish LLMs with illustrative examples.

Opening Statement. As first part of the prompt, \mathcal{P}_o contains a high-level instruction: "You are a knowledge graph constructor, need to synthesise relation extraction agent, named entity recognition agent, and event extraction agent to constitute an extraction collaborative team, which guides the agents to refine their results by referring to the extraction answers of others."

Task Definition. The task description \mathcal{P}_t can be further decomposed into three components, as exemplified by the RE agent:(1) The first sentence of the task description, "You are an excellent

Algorithm 1: The Optimization Process of CooperKGC on an arbitrary input text

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Input: Input Text  $\mathcal{X}$ , Expert Nodes  $\mathcal{A}$ , Communication Edges  $\mathcal{E}$ , Communication Unit  $\mathcal{C}$ , Round  $\mathcal{N}$ 
Output: KGC result  $\mathcal{Y}^i$  for each  $a_i \in \mathcal{A}$ 
for  $a_i \in \mathcal{A}$  do
  /* Initial extraction results */
   $r_0^i = \mathcal{F}_0^i(\mathcal{X} || \mathcal{P}_o, \mathcal{P}_t, \mathcal{P}_c); d_0^i = \mathcal{S}(r_0^i);$ 
end
for  $t = 1; \mathcal{N}$  do
  for  $a_i \in \mathcal{A}$  do
    /* Replicas delivery by edges */
     $\mathcal{D}_{t-1}^i \leftarrow \text{Transfer}(e_{m,i}), \forall i, e_{m,i} = (a_{t-1}^m, a_t^i) \in \mathcal{E};$ 
    /* Refine results by referring others */
     $r_t^i = \mathcal{F}_t^i(\mathcal{X} || \mathcal{D}_{t-1}^i || \mathcal{P}_o, \mathcal{P}_t, \mathcal{P}_c); d_t^i = \mathcal{S}(r_t^i);$ 
  end
end
/* Extract final answer, filter  $d_t^i$  whose format does not comply with the constraints */
 $\mathcal{Y}^i \leftarrow \text{filter\_ans}(d_t^i | a_t^i \in \mathcal{A}, \mathcal{C}, \mathcal{X});$ 

```

expert in relation extraction." is a constant that tells the LLM that it needs to focus on the relation extraction task; (2) The second sentence defines the output format of the task: "The relation extraction task is given a list of relations in the format (Relation Type: [Head Entity Type, Tail Entity Type]) You need to extract the relation type, the corresponding head and tail entities that may be included in the raw text, or answer NO if they do not exist. Each result is returned as a tuple, e.g. [(head entity 1, relation type 1, tail entity 1), (head entity 2, relation type 2, tail entity 2), ...]". (3) The third sentence points to a specific list of relation types: "The list of constrained relations is: [#Relation 1: [#Head Entity Type 1, #Tail Entity Type 2]...]".

In-context Demonstration. Some studies [29, 32, 56] show improvements in contextual learning by selecting few-shot demonstrations based on similarity. Our contextual prompts \mathcal{P}_c are introduced as N-way K-shot sampling of the demonstration samples $\mathcal{M} = N \times K$, providing direct evidence about the task and references to predictions. However, limited by the input tokens of the LLMs, a single prompt may not contain all supported instances, so we use a sentence embedding similarity-based approach to select the M examples with the closest Euclidean distance as contexts.

4.3 Collaborative Interaction Optimization

For devising intelligent agent optimization methods, ChatIE [62] introduces an innovative approach centered on task decomposition and the selection of pertinent extraction objects through two-stage artificial templates. Departing from the conventional strategy of devising fixed-stage thinking rounds tailored to a singular task, we reach to the periphery of the age-old adage, "Two heads are better than one." In the context of team collaboration optimization,

Table 2: F1-score results for 3 KGC tasks (NER, RE, EE) on the 8 datasets. The highest scores are in bold, and the underline represents the second-best-performing method. Note that the baseline model results are rerun with consistent settings.

Model	NER			RE			EE	
	Conllp	OntoNotes5.0	MSRA	NYT11-HRL	RE-TACRED	DUIE2.0	ACE05	DUEE1.0
AutoKG (0-shot)	50.6	40.4	56.8	12.5	17.2	26.9	20.7	68.7
ChatIE (0-shot)	58.4	47.5	<u>57.7</u>	37.5	43.9	68.4	29.7	72.0
CoT-ER (0-shot)	<u>60.1</u>	<u>52.6</u>	57.3	<u>45.3</u>	<u>44.2</u>	<u>68.7</u>	<u>43.1</u>	<u>73.1</u>
AutoKG (1-shot)	55.3	40.9	56.8	26.5	22.5	43.6	26.9	71.2
ChatIE (1-shot)	<u>61.3</u>	49.2	<u>59.2</u>	44.7	47.5	70.2	31.2	<u>74.2</u>
CoT-ER (1-shot)	<u>61.1</u>	<u>53.7</u>	58.7	<u>47.4</u>	<u>48.3</u>	<u>71.5</u>	<u>45.3</u>	74.1
CooperKGC (0-shot)	61.3(+10.7)	53.8(+13.4)	60.2(+3.4)	45.7(+33.2)	47.1(+29.9)	72.2(+45.3)	47.2(+26.5)	79.5(+10.8)
CooperKGC (1-shot)	61.5(+6.2)	55.4(+14.5)	60.9(+4.1)	49.2(+22.7)	51.2(+28.7)	73.6(+30.0)	47.5(+20.6)	81.3(+10.1)

the need for meticulous decomposition design diminishes, as proficient agents specializing in diverse domains engage in reflective interactions, honing their responses organically. As shown in Algorithm 1, after collecting replicas by other expert agents, we further provide collaboration prompts \mathcal{P}_v : The relation extraction answer you gave in the last round of collaboration was "##LAST_ROUND_RESULT##". The answer given by the NER expert agent in the knowledge graph construction team was "##NER_RESULT##". The EE expert agent gave the answer that comes out is "##EE_RESULT##". You should refer to the answers of other team members to add or delete some of your answers, and give credible reasons. If no modification is needed, please copy the answers from the previous round." Following ample interactions, the ultimate result materializes through the filtration of responses that deviate from the prescribed output format constraints (Section 3.1).

5 EXPERIMENTS

We conduct comprehensive experiments to evaluate the performance by answering the following research questions:

- **RQ1:** How does our CooperKGC perform through teamwork when competing against SOTA?
- **RQ2:** What is the impact of the expert agents and the communication rounds in multi-round interactions in teamwork?
- **RQ3:** What are the benefits of replicas delivery simplification and customized expert knowledge background?
- **RQ4:** How effective is the proposed CooperKGC in extracting different types of entities, relations and events?

5.1 Experiment Settings

5.1.1 Dataset. As to the NER task, we conduct experiments on the following popular benchmark: **Conllpp** [60], **OntoNotes5.0** [42] and **MSRA** [19]. The Conllpp dataset is a modified version of the Conll2003 [45] and contains 4 entity types. OntoNotes5.0 is an English NER dataset containing 18 types of named entities. MSRA dataset is a Chinese named entity recognition dataset for the news field and contains 3 entity types. For RE task, we conduct experiments on the following popular benchmark: **NYT11-HRL** [52], **Re-TACRED** [49], and **DUIE2.0** [24]. NYT11-HRL is a pre-processed version of NYT11 [14] and contains 12 pre-defined relation

types. Re-TACRED is a notably enhanced version of the TACRED dataset [73] for relation extraction which contains over 91 thousand sentences spread across 40 relations. DUIE2.0 is the industry’s largest schema-based Chinese RE dataset and contains 48 predefined relation types. Some of the objects in the triples have multiple attributes, called complex-object values. There are two standard EE datasets: **ACE05** [55] and **DUEE1.0** [25]. The ACE05 dataset provides event annotations in document and sentence levels from a variety of domains by defining 33 event types and 35 role types. DUEE1.0 dataset is a Chinese event extraction dataset released by Baidu, which contains 65 event types.

5.1.2 Baselines. In our experimental framework, we opt for **AutoKG** [74] as the implementation of Vanilla LLMs for KGC realm, which defines an end-to-end extraction workflow through the manual templates. Expanding on this foundation, **ChatIE** [62] refines the extraction process using a two-round method. Taking RE as an example, this method entails the initial extraction of the relation, followed by the output of the associated entity span. This sequential approach mirrors a cognitive model’s thought process, explicitly delineating the steps of task decomposition. Further, **CoT-ER** [32] introduces an explicit evidence reasoning method, characterized by three rounds of processing. In the first and second rounds, the LLM is required to output concept-level entities corresponding to head and tail entities. Subsequently, in the third round, the extraction of relevant entity spans occurs, establishing a specific relationship between these two entities with explicit evidence.

5.1.3 Evaluation Protocols. For the NER task, results is assessed using micro F1, with the predicted entity’s span should align precisely with the groundtruth, and the entity type should be an accurate match. Shifting to the RE task, the standard micro F1 metric is adopted for assessment. Correctness is contingent upon the accuracy of both the subject and object entity spans, coupled with the correct identification of the relation type. For the EE task, micro F1 is applied on the ACE05 dataset, necessitating the predicted event triggers and arguments to precisely align with the groundtruth. While on the DUEE1.0 dataset, the F1-measure relies on word-level matching, ensuring consistency in identification and classification of event triggers and arguments.

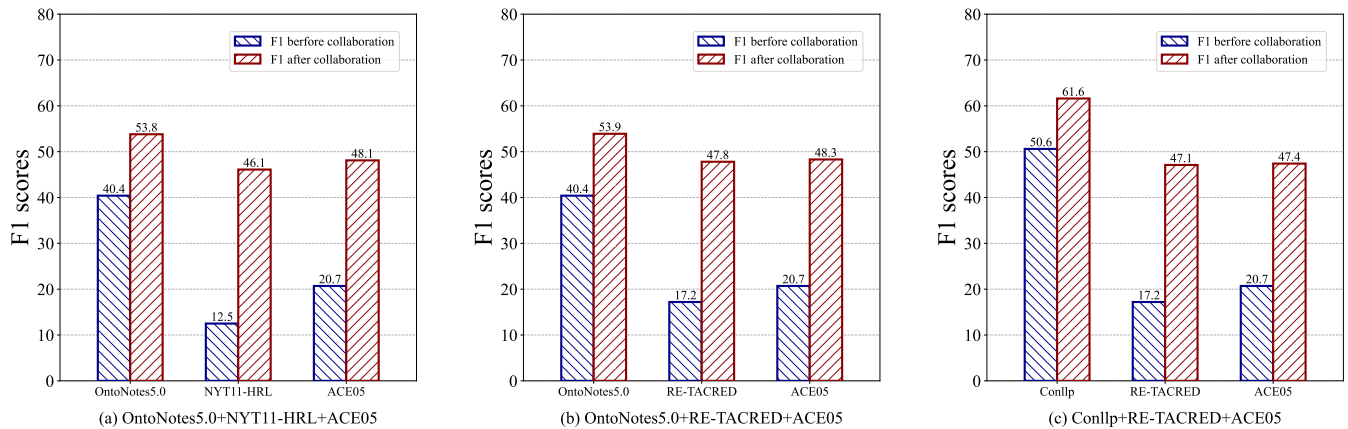


Figure 3: Results of equipping KGC agents with different expert knowledge backgrounds.

5.2 Performance Comparison with SOTA (RQ1)

In our study, we present comprehensive results from both 0-shot and 1-shot experiments conducted across 8 datasets. Note that due to API cost considerations, each experiment is conducted with 100 samples from the test/valid set and the results are evaluated using the standard micro F1. To facilitate fair comparisons, we adopt the "gpt-3.5-turbo" API as the default LLM backend for both baseline models and our proposed methods. The "temperature" parameter is set to 0.0, indicating the stable output of GPT-3.5, while we report the average results of three runs for all experiments. Within our method, the maximum of rounds to 4, and the number of KGC team members is fixed to 3. For the English dataset, the default customized expert knowledge background for the NER task is based on Conllpp, the RE task is NYT11-HRL, and the EE task is ACE05. Similarly, for the Chinese dataset, the NER task is based on MSRA, the RE task is DUIE2.0, and the EE task is DUIE1.0. Taking the OntoNotes5.0 dataset evaluation as an example, our team members' expert knowledge background is informed by the specifications of OntoNotes5.0, NYT11-HRL, and ACE05. This consistent methodology ensures a coherent and standardized approach across diverse datasets and tasks.

In Table 2, we report the F1-score results for 3 KGC tasks on the 8 datasets. Observations are as follows:

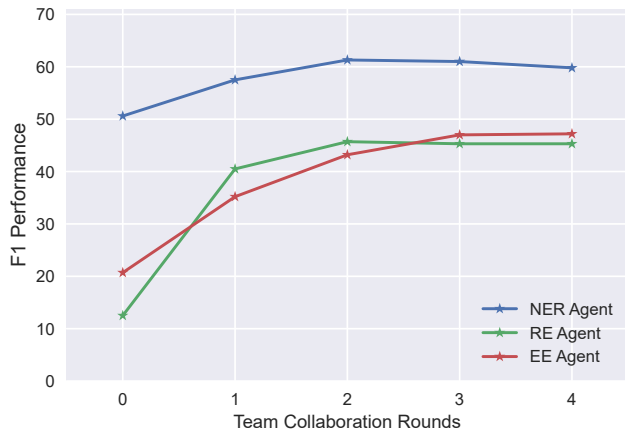
(1) CooperKGC improves the overall performance in diverse tasks. As can be seen from the NER task results, CooperKGC outperforms the vanilla LLM extraction method (AutoKG) in the 0-shot setting, where on Conllp dataset improved by 10.7, OntoNotes5.0 improved by 13.4, and MSRA improved by 3.4. Similarly, CooperKGC shows a general improvement in the 1-shot setting, which indicates that our method achieves significant improvements in both zero-shot and few-shot learning scenarios. In addition, CooperKGC is significantly higher than the baseline on all 8 datasets and 3 types of tasks, illustrating the advantages of the collaborative architecture. As compared to a single execution, the teamwork prompt strategy shows the benefits of associating different information extraction tasks. We believe that part of the improvement can be attributed to the multipath architecture based on extraction information sharing, which allows for an objective

view of the opinions expressed by different experts. In contrast, for a simple extraction approach like AutoKG with a single round of LLM calls, on the one hand, the overly heavy information input for task comprehension and rule constraints poses a challenge for a single model. On the other hand there is a lack of sufficient inference steps for a self-debugging process. In our approach, multiple rounds of interactions alleviate this anxiety of requiring "hit-and-miss" reasoning, making it easier to explicitly identify erroneous intermediate feedbacks during the interactions.

(2) Teamwork is an effective implicit reasoning chain. Taking the NYT11-HRL dataset as an example, although ChatIE improved by 25.0 over the baseline in the 0-shot setting while achieving an improvement of 18.2 over the baseline in the 1-shot setting, we believe that the gain stems from decomposing the extraction process into two phases. Among the first stage is determining the types of relations involved in a given sentence, which often involves multiple relations in a single sentence. The second stage then designs triple extraction templates for each relation, and similarly a relation can involve multiple triples. This is a kind of explicit expression of "Let's Think Step by Step" [17], which clearly indicates the sub-tasks to be accomplished in each stage of LLM, and thus achieves improved results. Further CoT-ER uses side information to induce LLM to generate explicit evidence of relationship reasoning, resulting in an improvement of 32.8 over the baseline in the 0-shot setting, as well as an improvement of 20.9 over the baseline in the 1-shot setting. Intuitively, triple extraction can be viewed as a mapping of head-to-tail entity spans to relation-type reasoning. Therefore, we believe that the gain comes from more intensive bootstrapping of LLM-specific task-level and concept-level knowledge. CooperKGC outperforms both, with a 33.2 improvement in the 0-shot and a 22.7 improvement in the 1-shot setting. We believe that building collaborative teams contributes to "Brain Storming" [38], where each round of the brainstorming process is performed by the members of team. By collecting evidence from other members in each round of interactions, agent's responses is fine-tuned from the previous round. Although there is no reasoning path planned for LLM, this proactive optimisation shows more encouraging prospects than passive methods.

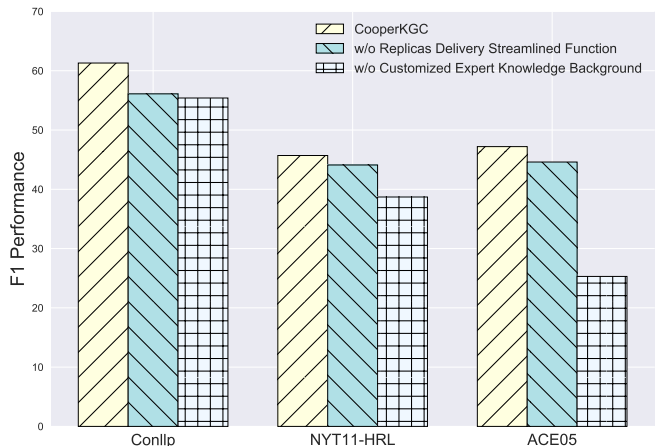
Table 3: Performance under different member assignments.

Team Members	Conllp	NYT11-HRL	ACE05
3-Agent	61.3	45.7	47.2
3-Agent + ONTONOTES	58.4	46.3	48.3
3-Agent + RE-TACRED	62.2	38.4	47.4
3-Agent + BOTH	58.6	38.9	48.4
3-Agent (ALL CONLLP)	60.8	-	-
3-Agent (ALL NYT-HRL)	-	44.9	-
3-Agent (ALL ACE05)	-	-	29.1

**Figure 4: Performance with Increased Rounds.**

5.3 Analysis of Team Members and Interaction Rounds (RQ2)

To further investigate the impact brought by the combination of intelligences with different expert knowledge backgrounds on team collaboration, we introduce an experiment to analyse the diverse combination of team members. Specifically, We experiment on 0-shot setting and the number of team members is fixed to 3. By replacing the expert knowledge backgrounds representing NER agent, RE agent, and EE agent, we analyse which kind of expert knowledge backgrounds (mainly the schema constraints in the task description \mathcal{P}_t) could produce better benefits for the team construction goals. Figure 3 shows the results of equipping KGC agents with different expert knowledge backgrounds, and we observe that combination b (OntoNotes5.0+RE-TACRED+ACE05) allows EE expert agents to achieve the best extraction performance, and the richer variety of relation types guided by RE-TACRED allows EE agents to discover more potential arguments compared with combination a. In addition, combination b achieves a more comprehensive improvement compared to combination c. We analyse the schema of OntoNotes5.0 versus Conllp and find that three of the entity categories are the same ("PER", "LOC", "ORG"), while the remaining 15 more specialised entity categories refine the "MISC" category in Conllp, which results in benefits in extraction performance for the RE-TACRED and ACE05 datasets. We therefore conclude that more specialised expert agents, i.e., equipped with fine-grained

**Figure 5: Ablation study of CooperKGC framework.**

schema constraints, can bring more insightful information to guide teamwork.

Another question is whether it is possible to equip with more agents to make more gains for our team. Table 3 shows the results of both kinds of experiments, the upper one is to add additional agents to the original team, and the results show that Team (3-Agent+BOTH) makes the extraction results of ACE05 improved by adding a NER Agent and a RE Agent. However, another risk is also demonstrated, in both Team (3-Agent+OntoNotes) and Team (3-Agent+RE-TACRED) it is observed that when more authoritative expert agents are introduced, it leads to a decrease in the extraction results of the agent for the same task, and this kind of unconscious opinion conformity is consistent with the concept of "Presentation of Self" [11] in sociology. In addition, inspired by "Self-consistency" [58], in the bottom of Table 3 we explore the difference between the performance of the self-consistent voting method and CooperKGC on a single task. Although the consistency method to some degree mitigates the randomness of the single agent producing the hallucinatory fact, it is nevertheless weaker than our results on all 3 representative datasets. We argue that a single perspective is unable to access the interactive information provided by other experts, and thus suffers from "Information Cocoons"[51].

Next, we provide an analysis of the impact of the number of collaboration rounds on multi-agent teams. In Figure 4, we increase the number of rounds for interaction between agents while fixing the number of agents to 3. We find that the performance of the algorithm also increases with the number of collaboration rounds in the first 2 rounds on all three types of tasks. However, the NER agent performance achieves its best in round 2, the RE agent in round 3, and additional collaboration by the EE agent over 3 rounds leads to a final performance similar to 3 rounds collaboration. Therefore, we believe that for tasks with simple extraction structures, too many interactions may lead to the introduction of undesirable hallucinations, hence a balance between performance and collaboration costs needs to be achieved on a task-specific basis.

Table 4: A qualitative example of CooperKGC on expert agent collaboration. Each expert absorbs a more detailed interactive view from different perspectives, leading to stronger knowledge selection, knowledge integration, and knowledge teamwork. Red text represents elements that conflict with groundtruth, and blue text represents elements that are updated compared to previous round’s result.

R	NER Agent	RE Agent	EE Agent
0	(LOC, Palestinian section of the border crossing)	(Palestinian section of the border crossing, location-located_in, Israeli troops) (Israeli troops, person-nationality, Palestinians)	{{Trigger Type: Conflict-Attack, Trigger Word: taken over, Arguments: (Attacker, Israeli troops),(Target: Palestinian section of the border crossing)}, {Trigger Type: Movement:Transport, Trigger Word: return, Arguments: (Destination, the Palestinian section of the border crossing)}}
1	(PER, Israeli troops), (LOC, border), (ORG, police) (PER, Six Palestinian police officers)	(Israeli troops, location-located_in, the Palestinian section of the border crossing), (Israeli troops, person-nationality, Israeli), (Six Palestinian police officers, person-nationality, Palestinians)	{{Trigger Type: Conflict-Attack, Trigger Word: uprising, Arguments: (Attacker, Israeli troops), (Place, the Palestinian section of the border crossing)}, {Trigger Type: Movement:Transport, Trigger Word: return, Arguments: (Destination, the Palestinian section of the border crossing)}}
2	(PER, Israeli troops), (LOC, border), (ORG, police), (PER, Six Palestinian police officers)	(Israeli troops, person-place_lived, the Palestinian section of the border crossing), (Israeli troops, person-nationality, Israeli), (Six Palestinian police officers, person-nationality, Palestinians)	{{Trigger Type: Conflict-Attack, Trigger Word: uprising, Arguments: (Attacker, Israeli troops), (Place, Israeli)}, {Trigger Type: Movement:Transport, Trigger Word: return, Arguments: (Destination, border), (Artifact, Israeli troops)}}
3	(PER, Israeli troops), (LOC, border), (ORG, police), (PER, Six Palestinian police officers)	(Israeli troops, person-place_lived, the Palestinian section of the border crossing), (Six Palestinian police officers, person-nationality, Palestinians)	{{Trigger Type: Conflict-Attack, Trigger Word: uprising, Arguments: (Attacker, Israeli troops), (Place, Israeli)}, {Trigger Type: Movement:Transport, Trigger Word: return, Arguments: (Destination, border), (Artifact, Six Palestinian police officers)}}
4	(PER, Israeli troops), (LOC, border), (ORG, police), (PER, Six Palestinian police officers)	(Israeli troops, person-place_lived, the Palestinian section of the border crossing), (Six Palestinian police officers, person-nationality, Palestinians)	{{Trigger Type: Conflict-Attack, Trigger Word: uprising, Arguments: (Attacker, Israeli troops), (Place, Israeli)}, {Trigger Type: Movement:Transport, Trigger Word: return, Arguments: (Destination, the Palestinian section of the border crossing), (Artifact, Six Palestinian police officers)}}

5.4 Ablation Study of CooperKGC (RQ3)

To further validate the rationality of the components, we undertake a comprehensive examination through two ablation experiments: "w/o Replicas Delivery Simplification Function" and "w/o Customized Expert Knowledge Background." As shown in Figure 5, the removal of simplification function led to a noticeable degradation in performance across all three datasets. We believe that besides bringing the advantage of reducing the length of token input, this filtered information method enhances the robustness of intra-team decision-making, avoids the noise distraction of individual thought processes, and makes team collaboration more concise and efficient. In the second experiment, we delved into the consequences of removing the tailored expert knowledge background. Although we retained plain schema guidance for each task, the lack of a self-cognitive prompt causes agents to be unskilled in locating the information from the text, consistent with research [5, 9, 21, 67] that assigning roles can significantly affect their generative behaviour. We argue that agents with different specialisations can collaborate efficiently with each other in performing complex tasks. Furthermore, This role-playing mechanism allows multi-agents to interact actively with each other for their own task goals, alleviating the monotonous confidence in their own responses.

5.5 Case Study of Collaboration Process (RQ4)

To illustrate the effectiveness of our proposed CooperKGC for collaborative interactions in KGC teams, Table 4 provides a qualitative example demonstrating the intermediate process. Note the CoT reflection process such as "After considering the extraction results of other agents..." is skipped, and the input sentence is an example of EE task "Six Palestinian police officers were allowed

to return to the Palestinian section of the border crossing, which had been taken over by Israeli troops shortly after the start of the uprising." we compare the results of the EE agent with the groundtruth, while the results of the NER agent and the RE agent are only for reference since there is no groundtruth. The observations are as follows: (1) **Knowledge Selection.** In Round 2, the EE agent borrows the *LOC* entity "border" newly discovered by the NER agent in the previous round and adds an argument (*Destination, border*) to the original answer; (2) **Knowledge Correction.** In the 1st round of interactions, the EE agent corrects the wrong trigger word "taken over", which indicates that the team members have the ability to provide self-feedback; (3) **Knowledge Aggregation.** Although the EE agent puts a wrong argument (*Destination, border*) in round 3, it rectifies the hallucination facts generated in the interim by eliciting LLM semantic comprehension during the interaction.

6 CONCLUSION AND FUTURE WORK

In this work, we have made an initial attempt to aggregate agents with different expert knowledge to form KGC team. Our findings reveal the impressive collaborative capabilities of LLM agents, demonstrating the possibilities of agent networks in mutually enhancing task performance. The human-like behaviours that emerge during collaboration resonate with sociological theories and effectively improve LLM performance in factuality, knowledge integration and intellectual reasoning. In the future, sociologically derived architectures could provide insightful inspirations. The rich variants of CooperKGC can be applied to multi-subject cognitive teams to solve more flexible collaborative tasks. In addition, as LLM evolves, understanding the adaptive combination patterns of team members will be critical to instructing more collaborative agent networks.

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