SOP – Tianyi Zhang

I am passionate about developing anthropomorphic agents to support underprivileged populations. Specifically, my endeavors modify current black-box language models (LMs) to **emulate human understanding and reasoning** procedure. Humans evolve sophisticated intelligence through explicit structured knowledge and symbolic systems (Tulving, E., 1985).[6,7] In contrast, a significant challenge with current LMs, including the SOTA GPT family, is their inability to automatically construct such structured and symbolic representations that humans rely on within their artificial neural networks. This deficiency, lacking intermediate symbolic representations to bridge neurons and language outputs, leads to widely criticized unreliable reasoning in LMs.

To alleviate it, my research **directs LMs to construct and reason with structured and symbolic representations**. My research trajectory begins with event extraction through question-answering and synthetic data augmentation techniques (Proj.4), followed by constructing event schemas using human-computer interaction (Proj.3). These efforts assist models to interpret structured knowledge graphs from unstructured text. Subsequently, I investigate the translation of natural language into agent-executable symbolic language utilizing a human cognition theory named ZPD (Proj.2). This work enhances the model's reliable reasoning capabilities via symbolic representations. Currently, my work explores pretraining LMs using a reconstruction loop that integrates both natural language and knowledge graphs (Proj.1). This approach embeds encoding-decoding skill, akin to human learning processes, into the LMs in the pretraining phase. Collectively, my research aims to advance artificial agents with human-like thinking abilities. Below, I will present these efforts in detail, along with potential future work (Sec.5).

1. Pretraining Language Models with Natural Language and Knowledge Graph Reconstruction Loop

Original text: New York is one of the most crowded cities in America

→ KG: (New York, located in, America), (New York, has, large population)

- **Problem-Solving:** The prevalent pretraining task, next token prediction, has been criticized by only capturing surface-level token correlations, rather than the logical reasoning inside the text. we propose a novel unsupervised pretraining framework that facilitates deeper knowledge embeddings of the text, including entities and relationships. Specifically, inspired from human learning procedure: information encoding and decoding, we compose an NL-KG-NL loop as an unsupervised pretraining task (similar to back-translation) (Fig 1).[5] Deeper semantic and logical knowledge from the text is incorporated into the embeddings when pretraining the LMs with these extraction and literalization skills.
- **Work Impact:** this pretraining framework: 1) enhances reasoning performance on downstream tasks, and 2) serves as a continued pretraining task for low-resource domains.

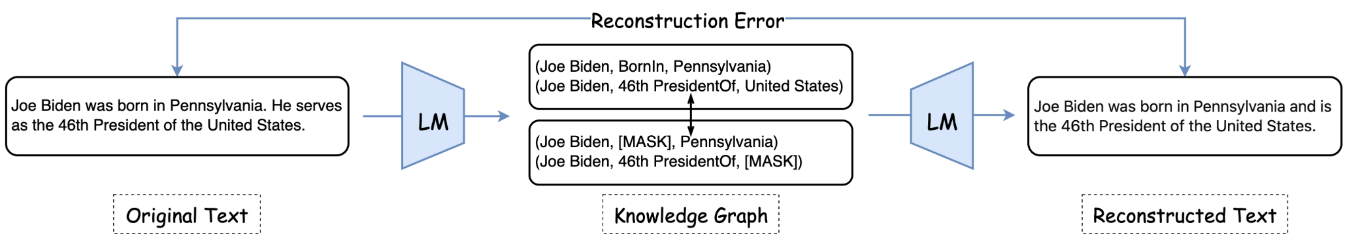


Fig 1. Pretraining LMs with NL-KG-NL reconstruction loop.

2. Proc2PDDL: Building Symbolic World Knowledge from Text for Reasoning

Domain action is a granular explanation of an action/event with pre-condition and effect.

E.g., Action go: pre-condition (I, at home); effect (I, at a restaurant)

- **Problem-Solving:** Previous works either use natural language as the means of reasoning or solely use generated codes to solve reasoning problems. Here, we utilize the knowledge incorporated in the natural language, such as wikiHow, and translate it to executable symbolic language, like PDDL. To solve this text2code task, **I view it as three consecutive basic skills building upon one another: entity identification, relation inference and knowledge translation, elicited from human cognition theory: Zone of Proximal Development**[8] (Fig 2).[3,4] It allowed GPTs to capture often-ignored implicit entity states, e.g., shape changed, in a schema.
- **Work Impact:** the executable and fine-grained symbolic representation of world knowledge enhance LMs' reasoning abilities and allow robots to gain open-domain comprehension from natural language text.

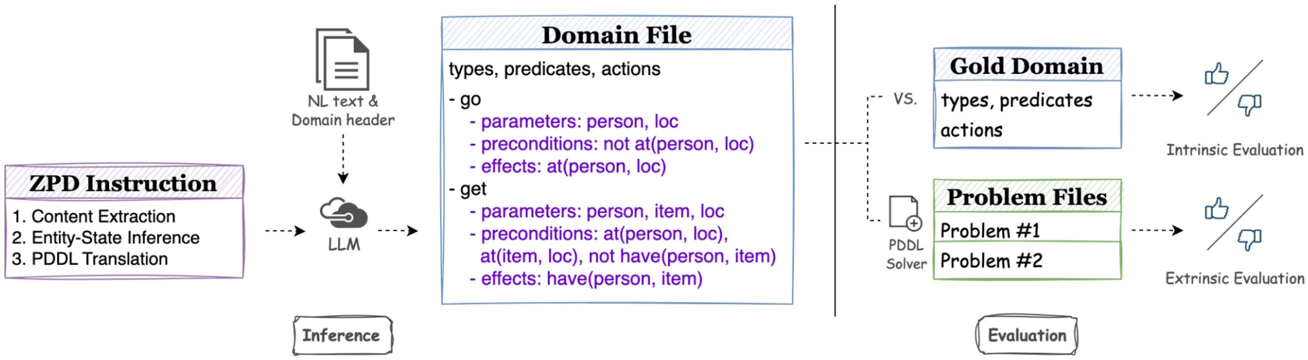


Fig 2. Proc2PDDL: performing text2code translation task with ZPD scaffolding.

3. Human-in-the-Loop Event Schema Induction

Event schema is a graphical depiction of event knowledge, e.g., "I go to a restaurant", followed by "I eat food".

- **Problem-Solving:** I joined this project when other groups had worked on it for years. I quickly caught up on the progress by discussing with professors and reading the previous documents. To manage the task effectively, I began by **summarizing the human reasoning patterns** from 11 annotated schemas (teacher)**, then progressed to auto-generation** (student). The process involved using GPTs to infer the details and merge the graphs iteratively. Despite their impressiveness in common sense, GPTs succumbed to intricate relations. While human annotation is precise but prohibitively onerous (≈ 1 hour/schema).[11] To strike a balance, I led the team to develop an interface supporting human-GPT interactive schema generations (≈ 15 mins/schema) (Fig 3).[2]
As a leader, I ensured both every member felt valuable in the group and efficient project outcomes as a sub-team in KAIROS. I navigated through accommodating **diverse interests, opinions, and levels of engagement**.
- **Work Impact:** Our demo was used by the UIUC group to collect data efficiently.

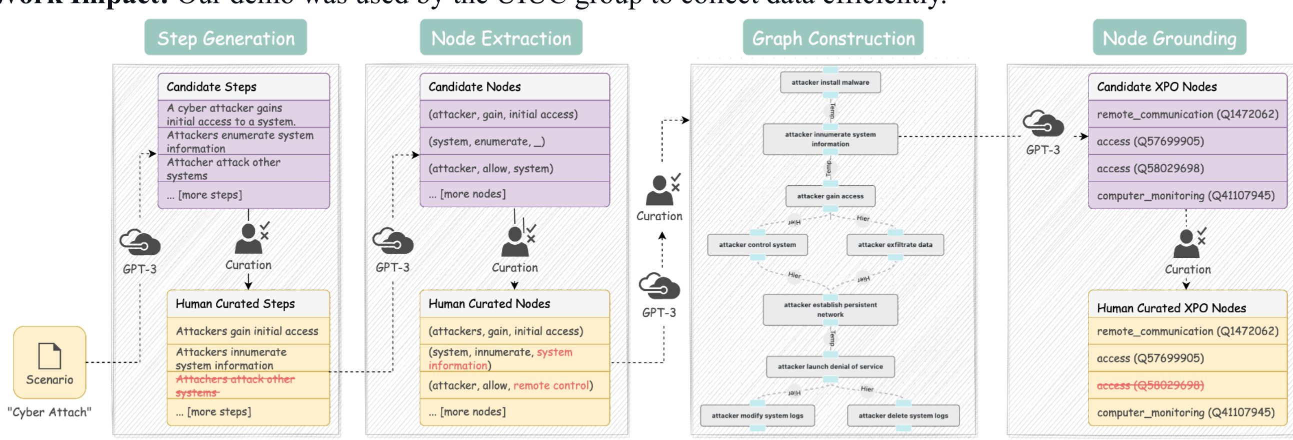
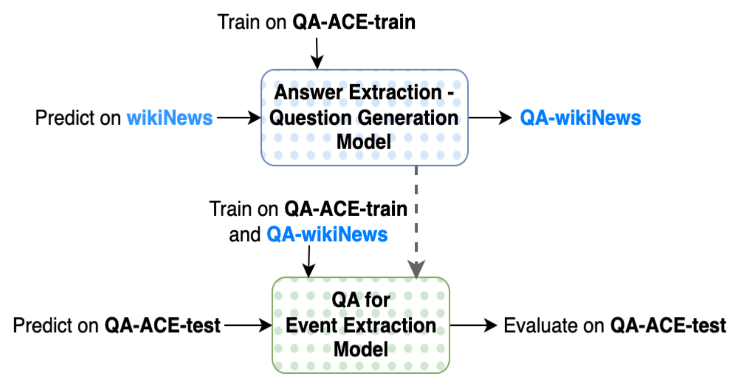


Fig 3. Human-GPT interactively generates an event schema in four stages from scratch.

4. Event Extraction with QA Data Augmentation

Event Extraction derives structured triples from unstructured text,
E.g., "I go to a restaurant." elicits a 'Travel' event: (trigger: go, person-arg: I, place-arg: restaurant).

- **Problem-Solving:** I applied a trigger-argument pipeline with RoBERTa where triggers underwent conventional BIO tagging, while arguments leveraged a unique Question-Answering (QA) approach. This strategy promoted information sharing of arguments and facilitated transfer learning from abundant QA datasets. However, the lack of in-domain annotation data hinders the performance. To resolve the bottleneck, **I introduced synthetic QA augmentation[9] to restrictive event contexts** (Fig 4).[1] I implemented an answer extraction-question generation (AE-QG w/ Bert-T5) framework. Not only did it circumvent the no-answer questions making up 60% of the inquiries, but it also proved notably efficient, our 8k synthetic data surpassing the performance of 80k SQuAD data as tested on the ACE.



- **Work Impact:** my work was incorporated in the BETTER pipeline.

5. Gazing Ahead: A Future Toward Anthropomorphic Intelligence (AI)

For me, the pursuit of Anthropomorphic Intelligence offers numerous promising research opportunities:

- First, continually enhance models' reasoning abilities with Reinforcement Learning (RL). Current RL methods, such as RLHF and DPO [17,18], enable LMs to reflect on natural language tokens, while RL in simulation environments primarily employ symbolic representations, including states and actions. In my view, LMs could benefit from reinforcement learning in an intermediate format—**structured representations**—such as **repeatable modules of events and concepts**. Particularly, LMs can be organized into two hierarchical functions: $LM_{procedure}$, which generates the graph of modules, and $LM_{semantic}$, which produces the specific knowledge in the module. Reinforcement signals derived from a piece of text can update both the graph structure in $LM_{procedure}$ and the content of each module in $LM_{semantic}$ (Fig 5). For instance, if a news article describes several related events and their details, $LM_{procedure}$ would update the weights of the elements in the graph, while $LM_{semantic}$ would acquire new knowledge about the reproducible events. These categorized functions allow language models to perform explicit reasoning on structural elements while maintaining detailed memorization within each module.

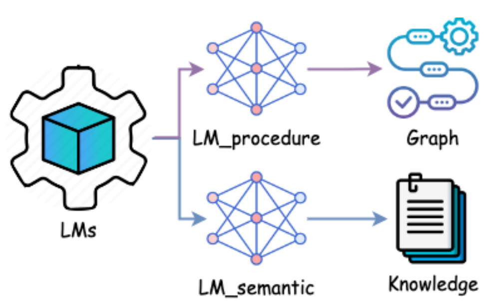


Fig 5. Hierarchical LMs with $LM_{procedure}$ and $LM_{semantic}$

- Second, explore multimodal training architecture. Studies in neuroscience suggest that distinct senses, e.g., vision, language, etc., are linked to central concepts through star networks. For instance, when we say 'bird', its image, definition, and other sensory associations immediately come to our mind (Fig 6). Accordingly, **cross-learning multimodal embeddings through grounded concepts** is promising. In my view, multimodal models should include dedicated channels or sub-models efficient in processing distinct signals while allowing for information exchange between them. Furthermore, the final embeddings could be projected into a common space, enabling comparability of the grounded concept across embeddings. To my knowledge, there are many works on multimodality, [14-16] but they fail to theorize their approaches and overlook the essence of grounding.

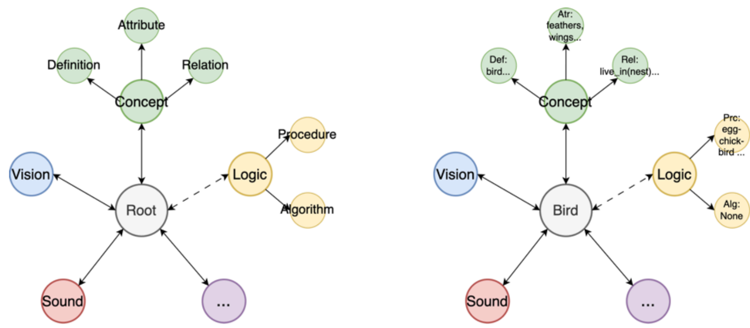


Fig 6. Star Network of Entity Bird

Every challenge I've faced has only deepened my love for this field, fueling my determination to make meaningful research progress. I would be honored to join the esteemed NLP lab here and to make contributions with my passion, expertise, and vision.

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