Tianyi Zhang

Email | Homepage | Google Scholar | GitHub

HIGHLIGHTS

- **Expertise:**

Natural Language Processing	5 years in MSE and beyond
Human Cognition & Education	6 years in B.S., M.Ed.

- **Research Experience:**

4 projects in 5 years:	Synopsis:
Event Extraction	DARPA BETTER, USA, 20-22, publication [6]
Schema Induction	DARPA KAIROS, USA, 22, leader, publication [5]
Natural to Symbolic Translation	AI2, USA, 23, member & leader, publication [2,3]
Pretraining with NL-KG Reconstruction	University of Bonn, Germany, 24-25, publication [1]

- **Research Interests:**
  Understanding and Reasoning in Natural and Symbolic Language
  Language Model Pretraining, Multimodality
  Other human cognition and NLP related fields, including Robotics, CV
  Happy to explore and confident to work well in varied tasks

EDUCATION

- **University of Pennsylvania** | Philadelphia, USA — Sept. 2018 – Dec. 2022
  MSE in Data Science — GPA: 3.97/4.00
  Advisor: Prof. Chris Callison-Burch

  M.Ed. in Learning Science and Technology — GPA: 3.91/4.00
  Advisor: Prof. Yasmin B. Kafai

- **Beijing Normal University** | Beijing, China — Sept. 2014 – Jul. 2018
  B.S. in Educational Technology — GPA: 88/100
  Advisor: Prof. Qian Fu

PUBLICATIONS

[1] IKnow: Instruction-Knowledge-Aware Continual Pretraining for Effective Domain Adaptation. — Paper in submission 2025
Zhang, T. *, Mai, F. *, Flek, L.
[paper] [poster] [oral]

[2] PROC2PDDL: Open-Domain Planning Representations from Texts. — NLRSE@ACL 2024
Zhang, T. *, Zhang, L. *, Hou, Z., Wang, Z., Gu, Y., Clark, P., Callison-Burch, C., and Tandon, N.
[paper] [poster] [oral]

[3] PDDLEGO: Iterative Planning in Textual Environments. — *SEM 2024
Zhang, L., Jansen, P., **Zhang, T.**, Clark, P., Callison-Burch, C., Tandon, N.
[paper] [oral]

[4] WorldWeaver: Procedural World Generation for Text Adventure Games. Wordplay@ACL 2024
Jin, M., Kaul, M., Ramakrishnan, S., Jain, H., Chandrawat, S., Agarwal, I., **Zhang, T.**, Zhu, A., Callison-Burch, C.
[paper]

[5] Human-in-the-Loop Schema Induction. ACL Demo 2023
Zhang, T. *, Tham, I. *, Hou, Z. *, Ren, J., Zhou, L., Xu, H., Zhang, L., Martin, L., Dror, R., Li, S., Ji, H., Palmer, M., Brown, S., Suchocki, R., and Callison-Burch, C.
[paper] [poster] [oral]

[6] Question-Answering Data Augmentation for Argument Role Labeling. 2022
[paper]

ACADEMIC SERVICE

- **Reviewer**
  INLG 2025, ACL 2025, IJCNLP-AACL 2023
- **Program Committee**
  INLG 2025

WORK EXPERIENCE

- **Visiting Scholar** — **Lamarr Institute** | University of Bonn, Germany — Sept. 2024 – Jul. 2025
  Advised by Prof. Lucie Flek
  See the Research Experience section for details

- **Research Assistant** — **NLP Group** | University of Pennsylvania, USA — May. 2022 – Jun. 2023
  See the Research Experience section for details
  An NLP Group | University of Pennsylvania — Mar. 2020 – Dec. 2022
  See the Research Experience section for details

- **Teaching Assistant** — **CIS522 Deep Learning** | University of Pennsylvania, USA — Jan. 2022 – May. 2022
  · Design course materials and teach deep learning models in CV, NLP, RL, etc.
  · Hold Office Hours and group discussions each week.

- **Data Analyst** — **SciStarter** | Philadelphia, USA — Sep. 2018 – Apr. 2019
  · Use the Python Pandas package to clean and analyze email log-in data (30,000 records).
  · Find the highest possibility of emails being checked is between 9 a.m. to 3 p.m., and within 1 day (over 80%). The most attractive topics are love, games, and high tech. The royalty of the subscriber is 50%.

RESEARCH EXPERIENCE

- **Lamarr Institute at University of Bonn** — Sept. 2024 – Jul. 2025
  Pretraining Language Model through Unsupervised Text and Knowledge Graph Loop
  · To enhance model's understanding and reasoning abilities on downstream tasks
  · Design pretraining pipeline imitating human learning: encoding-decoding and key phrase memorization
  · Train LLMs on masked phrases and NL-KG-NL reconstruction objectives
  · Improve faithfulness and interpretability of black-box LMs
  · Publication [1]: " IKnow: Instruction-Knowledge-Aware Continual Pretraining."
- **NLP Group at UPenn** — May. 2022 – Jun. 2023

Natural to Symbolic Reasoning

- To reason on events unfold: infer events with fine-grained entity-state
- Translate open-domain Natural Language text (wikiHow) to Symbolic Language (PDDL) with GPT-4
- Decompose the task into three stages: extraction, inference, and translation
- Identify strong text extraction and entity-state inference abilities with complex wikiHow text (~5000 words)
- Acknowledge a weak translation capability to predefined symbolic predicates
- Improve the entity-state tracking using CoT and instructions on translation.
- Publication [2,3]: "PROC2PDDL: Open-Domain Planning Representations from Texts."

Event Schema Induction

- To understand event relations: (semi-) automatically create event schema in high quality
- Design the scaffolds (cause, plan, procedure, effect, etc.) for GPT-3
- Apply SRL and constituency parsing to summarize and extract structured events
- Build schema graphs by adding temporal relations to the events
- Iteratively prompt LM and merge graphs
- Design interface for human - GPT interactive schema generation
- Improve accuracy and efficiency (1 hour to 15 mins per schema) and adopted by the UIUC group
- Publication [5]: "Human-in-the-Loop Schema Induction."

• An NLP Group at UPenn — Mar. 2020 – Dec. 2022

Event Extraction

- To understand atomic events: extract events with 'who does what to whom'
- Identify and classify event triggers using sequence tagging
- Design a pipeline: BIO identify - event type classify model to replace the joint model
- Improve performance with transfer learning on target language dataset, e.g., OntoNotesArabic
- Identify and classify event arguments using QA
- Design fixed questions for each argument role and convert the argument role labeling task to the Question-Answering task
- Build a pipeline model: has/no answer classification + has answer identification to replace has-and-no-answer joint model
- Improve performance with transfer learning on auxiliary QA datasets, e.g., SQuAD, QAMR

Event Data Augmentation

- To overcome the deficiency of event annotation data
- Design a pipeline approach: answer extraction (AE) and question generation (QG)
- Train AEwSRL-QG Bert-T5 model to extract QA pairs from unlabeled event text
- Evaluate the augmented data on QA event extraction model
- Prove the effectiveness of the data augmentation approach (8k synthetic data exceeds 80k SQuAD data test on the ACE)
- Publication [6]: "Question-Answering Data Augmentation for Argument Role Labeling."