1 Curriculum Vitae

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1.1 Education

09/2009-02/2016	PhD	Computer Science	Hong Kong University of Science and Technology
09/2005-07/2009	Bachelor	Computer Science	University of Science and Technology of China

1.2 Work experience

11/2017 - presently	Assistant Professor School of computer Science and Software Engineering, Shenzhen University
02/2020 - 06/2020	Guest Lecturer Department of CSE, Hong Kong University of Science and Technology
03/2016 - 10/2017	Post-doctoral Research Fellow Department of IELM, Hong Kong University of Science and Technology

1.3 Selected awards

- Winner of Verbal Track, IJCAI Machine Automated IQ Test Competition (MAIQ), 2021
- Winner of Diagram Track, IJCAI Machine Automated IQ Test Competition (MAIQ), 2021
- The Second Prize in Guangdong Teaching Innovation Contest (Shenzhen University), 2022
- Outstanding Undergraduate Course Award, Shenzhen University, 2021
- Annual Excellence Award, Shenzhen University, 2020
- Tencent “Rhino-bird” Open Fund Young Researcher Award, 2019
- Best New Faculty Award, School of CSSE, Shenzhen University
- Excellence Award, “Torch” Teaching Program, Shenzhen University, 2019
- Second Price of the 9th SZU Teaching Competition, School of CSSE, Shenzhen University, 2019

- Shenzhen “Peacock” High-level Talent (Category C), 2018

1.4 Funded research projects

- PI, *Theory and Application of Nonmonotonic Reasoning in Characterizing Action Languages*, National Natural Science Foundation of China (NSFC), Youth Research Program, 2019-2021
- PI, *Integrating Knowledge Representation and Reasoning into Deep Reinforcement Learning*, GuangDong Basic and Applied Basic Research Foundation, General Program, 2022-2024
- PI, *Embedding Explicit Knowledge in Deep Reinforcement Learning*, Finance Commission of Shenzhen Municipality, Open Project, 2020-2022
- PI, *Knowledge-Enhanced Deep Reinforcement Learning*, High-level University Construction Fund of Shenzhen University, 2019-2020
- PI, *Logic Based Artificial Intelligence in Game Playing*, Tencent Open Fund, 2019-2020
- PI, *Nonmonotonic Reasoning in Deep Reinforcement Learning*, Shenzhen University start-up fund, 2017-2019.
- Co-I, *Crowd situation calculus based on multi-dimensional deep-perception information*, the Joint Funds of National Natural Science Foundation of China (NSFC), Key Program, 2021-2024

1.5 Professional service

- Senior member/member of Program Committee for
  - AAAI Conference on Artificial Intelligence (AAAI) 2022, 2021, 2020, 2019, 2018, 2015
  - International Joint Conference on Artificial Intelligence (IJCAI) 2022, 2021, 2020, 2019, 2018
  - The Joint Conference of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (ACL-IJCNLP) 2022, 2021
  - The Conference on Neural Information Processing Systems (NeurIPS) 2021
  - The Conference on Empirical Methods in Natural Language Processing (EMNLP) 2021, 2020
  - International Conference on Principles of Knowledge Representation and Reasoning (KR) 2014, 2012
- Local chair for International Conference on Edge Computing and IoT (EAI ICECI) 2021
- Reviewer for
  - Machine Learning

- AAAI Conference on Artificial Intelligence (AAAI) 2022, 2021, 2020, 2019, 2018, 2015
- International Joint Conference on Artificial Intelligence (IJCAI) 2022, 2021, 2020, 2019, 2018
- The Joint Conference of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (ACL-IJCNLP) 2022, 2021
- The Conference on Neural Information Processing Systems (NeurIPS) 2021
- The Conference on Empirical Methods in Natural Language Processing (EMNLP) 2021, 2020
- International Conference on Principles of Knowledge Representation and Reasoning (KR) 2014, 2012

1.6 Invited talk

- Leveraging Human Intelligence in Machine Learning for NLP, on *The 2nd Macau Symposium on Linguistics*, Macau University, Dec. 4th, 2021
- Natural language processing: tasks, models and applications, on *The 2nd Interdisciplinary frontier Forum*, BNU Zhuhai, Nov. 24, 2021
- Leveraging Human Intelligence in Machine Learning for NLP, on *The 1st Macau Symposium on Linguistics*, Macau University, Dec. 4th, 2020

1.7 Teaching experience

	University	**Students**	**Course**	**Evaluation**
2020 Fall	SZU	Undergraduate	Discrete Mathematics	93.8/100
2020 Fall	SZU	Undergraduate	Natural Language Processing	85.2/100
2020 Spring	HKUST	Master	Natural Language Processing	-
2020 Spring	SZU	Undergraduate	Compilers	85.7/100
2019 Fall	SZU	Undergraduate	Discrete Mathematics	94.6/100
2019 Spring	SZU	Undergraduate	Compilers	100/100 (Top 0.7%)
2018 Fall	SZU	Undergraduate	Discrete Mathematics	93.6/100 (Top 9%)
2018 Spring	SZU	Undergraduate	Programming Languages	82.7/100

2 Publication List

Co-first author#, Corresponding author*

2.1 Published journal and conference papers

[1] **Haodi Zhang**, Zhichao Zeng, Keting Lu, Kaishun Wu, Shiqi Zhang. Efficient Dialog Policy Learning by Reasoning with Contextual Knowledge. *Proceedings of AAAI*, 2022 (CCF-A, Accepted)

[2] Junyang Chen, Mengzhu Wang, **Haodi Zhang**, Zhiguo Gong, Zhidan Liu, Kaishun Wu, Victor Leung, From Where and Where To Go: Deep User Interest Exploration for Sequential Location Recommendation. *IEEE Transactions on Neural Networks and Learning Systems*, 2022 (CCF-B, Accepted)

[3] **Haodi Zhang**, Zhenhao Chen, Junyang Chen, Yi Zhou, Defu Lian, Kaishun Wu and Fangzhen Lin. Dynamic Decision Making Framework Based on Explicit Knowledge Reasoning and Deep Reinforcement Learning (In Chinese). *Journal of Software*, 2022 (CCF-A, Accepted)

[4] Sheng Luo, **Haodi Zhang**, Qifan Li and Kaishun Wu. Knowledge-Assisted DRL for Energy Harvesting Based Multi-Access Wireless Communications, *Proceedings of IEEE HPCC*, 2022 (CCF-B, Accepted)

[5] Chen Zhang#, **Haodi Zhang#***, Qifan Li, Kaishun Wu, Di Jiang, Yuanfeng Song, Peiguang Lin, and Lei Chen. Burstiness-Aware Web Search Analysis on Different Levels of Evidences. *IEEE Transactions on Knowledge and Data Engineering* (TKDE), 2021 Early Access. (CCF-A, JCR Q1)

[6] Chen Zhang#, **Haodi Zhang#***, Weiteng Xie, Nan Liu, Kaishun Wu and Lei Chen. Where To: Crowd-Aided Path Selection by Selective Bayesian Network. *IEEE Transactions on Knowledge and Data Engineering* (TKDE), 2021 Early Access. (CCF-A, JCR Q1)

[7] Chen Zhang#, **Haodi Zhang#***, Weiteng Xie, Nan Liu, Qifan Li, Kaishun Wu, Di Jiang, Peiguang Lin and Lei Chen. Cleaning Uncertain Data with Crowdsourcing - a General Model with Diverse Accuracy Rates. *IEEE Transactions on Knowledge and Data Engineering* (TKDE), 2021 Early Access. (CCF-A, JCR Q1)

[8] Zhidan Liu, Junhong Zheng, Zengyang Gong, **Haodi Zhang** and Kaishun Wu. Exploiting Multi-source Data for Adversarial Driving Style Representation Learning. *Proceedings of 26th International Conference of DASFAA*, 2021:491-508. (CCF-B)

[9] Shan Wang*, Zhao Chen, **Haodi Zhang***, Macau's Vocabulary Growth in the Recent Ten Year (In Chinese). *Proceedings of the 20th Chinese National Conference on Computational Linguistics*, 2021:350-360.

[10] Hao Ren, Aslan B. Wong, Wanmin Lian, Weibin Cheng, Ying Zhang, Jianwei He, Qingfeng Liu, Jiasheng Yang, Chen Jason Zhang, Kaishun Wu, **Haodi Zhang***. Interpretable Pneumonia Detection by Combining Deep Learning and Explainable Models with Multisource Data. *IEEE Access* 9:95872-95883, 2021. (JCR Q1)

[11] Zihang Gao, Fangzhen Lin, Yi Zhou, Hao Zhang, Kaishun Wu, **Haodi Zhang***. Embedding High-Level Knowledge into DQNs to Learn Faster and More Safely. *Proceedings of the AAAI Conference on Artificial Intelligence* (AAAI short paper) 2020:13608-13609.

[12] **Haodi Zhang**, Di Zhan, Chen Jason Zhang, Kaishun Wu, Ye Liu, Sheng Luo. Deep Reinforcement Learning-Based Access Control for Buffer-Aided Relaying Systems With Energy Harvesting. *IEEE Access* 8:145006-145017, 2020. (JCR Q1)

[13] Yusen Liu, Fangyuan He, **Haodi Zhang**, Guozheng Rao, Zhiyong Feng and Yi Zhou. How Well Do Machines Perform on IQ tests: a Comparison Study on a Large-Scale Dataset. *Proceedings of International Joint Conference on Artificial Intelligence* (IJCAI), 2019:6110-6116. (CCF-A)

[14] Fangyuan He, Yi Zhou, **Haodi Zhang**, Zhiyong Feng. Dual-enhanced Word Representations Based on Knowledge Base. *International Semantic Web Conference* (ISWC short paper), 2018.

[15] **Haodi Zhang**, Fangzhen Lin. Characterizing causal action theories and their implementations in answer set programming. *Artificial Intelligence* (AIJ) 248:1-8, 2017. (CCF-A, JCR Q1)

[16] **Haodi Zhang**, Yu Wang, Xiangtong Qi, Weiping Xu, Tao Peng, Shucheng Liu. Demo: An intent solver for enabling intent-based SDN. *IEEE INFOCOM* (short paper) 2017:13608-13609.

[17] **Haodi Zhang**, Fangzhen Lin. Mapping Action Language BC to Logic Programs: A Characterization by Postulates. *Proceedings of the AAAI Conference on Artificial Intelligence* (AAAI), 2016:1116-1123. (CCF-A)

[18] **Haodi Zhang**, Fangzhen Lin. Characterizing Causal Action Theories and Their Implementations in Answer Set Programming: Action Languages B, C, and Beyond. *Proceedings of International Joint Conference on Artificial Intelligence* (IJCAI), 2015:3285-3291. (CCF-A)

2.2 Preprints (arXiv-articles and articles accepted subject to minor or major revision)

[1] **Haodi Zhang**, Zihang Gao, Yi Zhou, Hao Zhang, Kaishun Wu, Fangzhen Lin . Faster and Safer Training by Embedding High-Level Knowledge into Deep Reinforcement Learning. *arXiv* abs/1910.09986.

3 Research Statement

My research interests include both *symbolic* and *sub-symbolic* AI approaches, especially their combination and application in interdisciplinary fields, such as *data-driven healthcare*, *cognitive science*, *AI in entertainment* and *natural language processing*. Symbolic methods usually have high reliability, solid theoretical basis and full interpretability, but suffers from high computational cost and domain dependency. Sub-symbolic AI approaches such as deep learning have been successfully used in many dynamic decision making domains, especially those with very large state spaces. However, these approaches based on artificial neural networks are usually data sensitive, and not easily explainable. The central theme driving my work is to search for effective and efficient ways of combining knowledge-driven approaches with data-driven ones, to take their respective advantages in AI tasks.

3.1 Previous research

My previous research balanced both theory and system. My early work on nonmonotonic reasoning and action theories mainly focused on how the knowledge should be represented and reasoned with for different purposes. My recent work combining knowledge representation and reasoning (KRR) with deep reinforcement learning shows promising improvement in several domains, such as game playing and dialogue management. I am also leading a cooperation project between Shenzhen University and a general hospital, introducing AI techniques, especially explainable AI approaches such as Knowledge graph, Formal logic and Bayesian networks, to medical treatment and computer-aided diagnosis. For Cognitive Science and Common-sense AI, we have built a large dataset and a competition platform of IQ test for AI agents. The dataset can be used as a general testbed for combining logic-based AI with machine learning.

In the following, I will introduce some of my previous and ongoing works in three aspects,

1. **Knowledge representation**: how the knowledge should be formally represented for different purposes.
2. **Knowledge utilization**: how the knowledge could be embedded into data-driven frameworks.
3. **Knowledge evaluation**: how an intelligent system trained with data and knowledge should be properly evaluated.

3.1.1 Knowledge representation

Formal reasoning about action has been a central topic in logic-based AI for a long time, and motivated much of the early work on nonmonotonic logics. The main theoretical difficulties have been the frame and the ramification problems. Current consensus in the community is that to solve the ramification problem, a notion of causality is needed. As a result, there has been much work on causal action theories, and a variety of languages and semantics have been proposed. These different approaches basically all agree when the set of causal rules is stratified, and in this case yields a complete action theory that can be represented, for example, by a set of successor state axioms. However, when there are cycles of dependencies in the rules, it is not always clear how these rules are going to be represented according to these different approaches, and what the correct results are supposed to be. This motivated me to find a systematic way to analyze and evaluate different action theories. As it turned out, what counts as a desirable model depends on what properties we want to have about causal theories. We successfully postulated the famous action languages B [1], C [2] and BC [3] in a uniform system with answer set semantics.

3.1.2 Knowledge utilization for machine intelligence

With proper representations of common sense or domain-specific knowledge, we also need effective ways to utilize the knowledge in data-driven models. In recent years, the interpretability of AI models has drawn much attention. It has been commonly accepted in AI community that the interpretability and transparency are very important for AI models in many applications. We explored different ways to leverage high-level knowledge reasoning in data-driven methods, to increase the transparency and interpretability of the models. The idea has been successfully deployed in the following four domains, the first two of which use common sense knowledge and the latter two use domain-specific knowledge.

Crowdsourcing

Common sense knowledge from human being is not always easy to explicitly represented. In a complex intelligence task, an alternative of representing the knowledge in explicit rules is to decompose the task into some easy questions to answer or decisions to make. Crowdsourcing is a commonly used approach to leverage human's common sense knowledge and reasoning to help automated systems to complete some tasks, such data merging, path selection, etc. We successfully deployed the crowdsourcing framework in data uncertainty cleaning [4]. We also used the same framework in best path selection, making use of crowdsourced answers from human beings to get better selection of best paths [5]. The same idea was also used in topic modeling and achieved good performance. The corresponding papers [6, 7] are under review for TKDE.

Dialogue management with contextual knowledge

Goal-oriented dialog policy learning algorithms aim to learn a dialog policy for selecting action languages based on the current dialog state. Many deep reinforcement learning methods have been used for dialog policy learning. However, although dialog is a domain with rich contextual knowledge, reinforcement learning methods are ill-equipped to incorporate the knowledge into the dialog policy learning process. We develop a deep reinforcement learning framework for goal-oriented dialog policy learning that learns user preferences from user goal data, and leverages commonsense knowledge from people. The developed framework has been evaluated using a realistic dialog simulation platform. Compared with baselines from the literature and the ablations of our approach, we see significant improvements in learning efficiency and the quality of the computed action policies.

Knowledge-guided deep reinforcement learning for game playing

Deep reinforcement learning such as DQN has been successfully used in many dynamic decision making domains such as game playing. However, DQN and its variants are not explainable, and the training time is also often very long and suffers from "cold start" - performing very badly at the beginning. To address some of the problems, we proposed a framework of Rule-interposing

Learning (RIL) [8,9] that embeds high level knowledge rules into the deep reinforcement learning. With some good rules, this framework not only can accelerate the learning process, but also keep it away from catastrophic explorations, thus making the system relatively stable even during the very early stage of training. Moreover, given the rules are high level and easy to interpret, they can be easily maintained, updated and shared with other similar tasks.

Knowledge-enhanced learning in communication

We investigated the use of deep reinforcement learning to maximize the long-term throughput of multi-access wireless communication systems. Specifically, we consider the scenario in which an access point (AP) without dedicated power supply harvests energy from the ambient environment and uses the harvested energy to deliver data packets to multiple users, where the optimal access strategy is approximated by using a double deep Q-network (DDQN). We use some domain knowledge about the optimal strategy to help the DDQN during training. With the help of the domain knowledge, access control strategies which can achieve a higher system throughput can be found by the knowledge-embedded DDQN and the pretraining process can effectively improve the learning efficiency. Experiment results [10, 11] showed that the transmission policy obtained by using our proposed model can achieve better performance.

3.1.3 Intelligence evaluation

Proper evaluation is also important for the combination of data-driven models and knowledge. AI benchmarking is an increasingly important task. As suggested by many researchers, Intelligence Quotient (IQ) tests, which is widely regarded as one of the predominant benchmarks for measuring human intelligence, raises an interesting challenge for AI systems. For better solving IQ tests by automated systems, one needs to use, combine and advance many areas in AI including knowledge representation and reasoning, machine learning, natural language processing and image understanding. Also, automated IQ tests provides an ideal testbed for integrating symbolic and sub-symbolic approaches as both are found useful here. Hence, we argue that IQ tests, although not suitable for testing machine intelligence, provides an excellent benchmark for the current development of AI research. Nevertheless, most existing IQ test datasets are not comprehensive enough for this purpose. As a result, the conclusions obtained are not representative. To address this issue, we create IQ10k [12], a large-scale dataset that contains more than 10,000 IQ test questions. We also conduct a comparison study on IQ10k with a number of state-of-the-art approaches.

3.2 Future work

For future work, I'll continue my exploration on how to better integrate knowledge-driven approaches in data-driven systems. In my opinion, the potential use of symbolic methods in data-driven systems are underestimated and their applications have not been fully developed. To be specific, I'll work on the following aspects for future work.

1. **Knowledge representation** In my previous work, non-monotonic logics, causal theories and answer set programming rules are used for knowledge representation. However there usually is a common assumption that the explicitly representable knowledge is always available. Moreover, the knowledge rule sets are not easy to acquire. A possible solution

is to try some other representations such as Knowledge Graph and Bayesian network, and Markov Logic Network, which are also explainable, and support scaled applications. More importantly, they can be automatically constructed from data sources. I'm working on embedding Bayesian network into a classifier for pneumonia detection, and using Markov Logic Network in dialog management.

2. **Knowledge utilization**

   - **Data and knowledge fusion by crowdsourcing.** Currently we have established a general crowdsourcing framework for optimization tasks in data fusion or data cleaning. Typically, a complex data fusion task is firstly decomposed into human intelligence tasks (HITs), and some of these HITs are selected to ask the crowd, and finally the answers from the crowd are used to systematically improve the data quality. A very interesting direction would be considering a hybrid crowd that consists of both humans and automated systems or algorithms.
   - **Knowledge representation and reasoning for reinforcement learning in Robotics.** With the successful preliminary exploration in game playing, we believe the RIL framework also applies in robotics. The task in real world for robots can be modeled as an Markov decision process, and the reinforcement learning approaches have been commonly used in robotics. Proper knowledge representation and reasoning with symbolic systems have potential to accelerate the learning progress and improve the performance.
   - **Explainable diagnosis in Computer-aided Healthcare.** Explanation is important for both doctors and patients in computer-aided healthcare. I'm leading a cooperation project between Shenzhen University and Guangdong Second Provincial General Hospital. I'm working on introducing AI techniques, especially explainable AI approaches such as Knowledge graph and Bayesian network to medical treatment and computer-aided diagnosis. Our preliminary experiment on pneumonia detection by combining deep neural network and Bayesian network with multi-sourced data shows good performance and interpretability.
   - **Dialog management with Knowledge Graph**. We have deployed non-monotonic reasoning to improve a DQN-based dialog policy learning. The logic tool of non-monotonic reasoning we used is Answer set programming (ASP). However, the ASP rules from human experts are costly to be scaled up. If we can make use of some large-scaled predefined knowledge graph in the learning process, the whole system of knowledge and learning will be more practical and efficient. I'm leading a project on domain-specific Knowledge graph construction and utilization for question answering tasks.

3. **Knowledge evaluation** Our dataset in [12] is a good testbed for machine intelligence. We plan to enrich the dataset with more intelligence test questions and diverse tasks, and to propose better evaluation metrics for the congitive intelligence of the AI models and systems.

[1] Haodi Zhang and F. Lin, "Characterizing causal action theories and their implementations in answer set programming: Action languages B, C, and beyond," in *Proceedings of the Twenty-Fourth International Joint Conference on Artificial Intelligence, (IJCAI)*, 2015, pp. 3285–3291.

[2] ——, "Mapping action language BC to logic programs: A characterization by postulates," in *Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence (AAAI)*, 2016, pp. 1116–1123.

[3] ——, "Characterizing causal action theories and their implementations in answer set programming," *Artificial Intelligence*, vol. 248, pp. 1–8, 2017.

[4] C. Zhang, Haodi Zhang*, W. Xie, N. Liu, Q. Li, K. Wu, D. Jiang, P. Lin, and L. Chen, "Cleaning uncertain data with crowdsourcing - a general model with diverse accuracy rates," *IEEE Transactions on Knowledge and Data Engineering (TKDE)*, 2021, Early Access.

[5] C. Zhang, H. Zhang*, W. Xie, N. Liu, K. Wu, and L. Chen, "Where to: Crowd-aided path selection," *IEEE Transactions on Knowledge and Data Engineering (TKDE)*, 2021, Early Access.

[6] C. Zhang, H. Zhang*, Q. Li, K. Wu, D. Jiang, Y. Song, P. Lin, and L. Chen, "Burstiness-aware web search analysis on different levels of evidences," *IEEE Transactions on Knowledge and Data Engineering (TKDE)*, Under Review.

[7] L. Qiu, H. Zhang*, W. Huang, C. Zhang, D. Jiang, K. Wu, and L. Chen, "Burstiness-aware web search analysis on different levels of evidences," *IEEE Transactions on Knowledge and Data Engineering (TKDE)*, Under Review.

[8] Haodi Zhang, Z. Gao, Y. Zhou, H. Zhang, K. Wu, and F. Lin, "Faster and safer training by embedding high-level knowledge into deep reinforcement learning," *CoRR*, vol. abs/1910.09986, 2019.

[9] Z. Gao, F. Lin, Y. Zhou, H. Zhang, K. Wu, and Haodi Zhang*, "Embedding high-level knowledge into dqns to learn faster and more safely," in *proceeding of the Thirty-Fourth AAAI Conference on Artificial Intelligence, (AAAI)*, 2020, pp. 13 608–13 609.

[10] H. Zhang, D. Zhan, C. J. Zhang, K. Wu, Y. Liu, and S. Luo, "Deep reinforcement learning-based access control for buffer-aided relaying systems with energy harvesting," *IEEE Access*, vol. 8, pp. 145 006–145 017, 2020.

[11] S. Luo, Y. Wang, H. Zhang, D. Zhang, Q. Li, and K. Wu, "Knowledge-embedded deep reinforcement learning for multi-access wireless communications with energy harvesting," *IEEE Internet of Things Journal (Under Review)*.

[12] Y. Liu, F. He, H. Zhang, G. Rao, Z. Feng, and Y. Zhou, "How well do machines perform on IQ tests: a comparison study on a large-scale dataset," in *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, (IJCAI)*, 2019, pp. 6110–6116.

4 Teaching Statement

The opportunity to teach and advise students is one of my strongest motivations to pursue an academic career in the university. Through the experience as the instructor of diverse undergraduate and graduate courses, I have gained a deep insight into circumstances under which students effectively learn and conduct research, and a teacher can efficiently facilitate their learning process. Within the years of teaching in Shenzhen University, my teaching greatly benefits from my passion to help students establish scientific worldview and learn scientific methodology. I am willing to take effort on mining and presenting essential implications and inherent connections of concepts and algorithms, and enriching the content with related edge-cutting research topics. I have received several teaching awards these years, for my good performance on some courses that used to be considered difficult and boring. I am excited about the opportunity to teach both undergraduate and graduate classes in HKUST Guangzhou.

4.1 Teaching philosophy

I believe that teaching has at least three kernel tasks. The first one is to impart knowledge, which is the basic task of teaching. The expectation of knowledge impartation is enlarge students' knowledge base. To accomplish it, the instructor should have deep and clear understanding of the knowledge itself, and deliver the knowledge in a well-designed and intuitive way. The second task is to teach methodology, which makes the students learn to learn. Knowledge imparted in courses may not be directly used in their future career, but the methodology they learned from the courses could potentially benefit their life and work in the future. The Third task of teaching, which is most important in my opinion, is to help the students establish belief in science and rationality, and to inspire them to explore unknown fields in a scientific and rational way. I want to take the course *Discrete mathematics* as an example. The first basic goal of this course is to teach systematic knowledge of formal logic, graphs and algebraic systems. The students are expected to well know the concepts of propositions, predicates, DNF, group theory, etc, and well master the classical algorithms such as shortest path selection. For a concept to teach, I usually 1) use a toy example to introduce the motivation of the concept, and 2) give a mathematical analysis on the formal definition, and 3) give more positive and negative instances and finally 4) conclude and discuss the boundary, the exceptions, and the connection with other concepts. The second goal is to teach them the formal methodology to express and solve a problem. For instance, most problem solving can be modeled as a reasoning process with formal logic. No matter what logic is used, the basic process of problem solving consists of the following steps, 1) formally represent the problem with the selected logic, including the premises and hypothetical conclusion, 2) explore or search for a formal reasoning sequence with the verified reasoning axioms, and 3) verify the reasoning result with semantic models. The third goal of the course is to help them to establish a belief on logical and rational methodology. Every scientific problem should be explored and discussed in a well-defined framework of logic. Otherwise, the discussion could easily become emotional and meaningless arguments.

4.2 Teaching interests

My past teaching and research experience has covered a wide range of topics in computer science including software engineering, programming languages, formal logics, artificial intelligence. I would be excited and interested in teaching courses on discrete mathematics, formal logic, compilers, artificial intelligence, and natural language processing. I am also qualified and ready to teach introductory computer science courses, and basic material on programming languages.

4.3 Teaching experience

I am currently supervising 10 Master's students and 8 undergraduate students in the School of Computer Science and Software Engineering at Shenzhen University, China. I have instructed 12 undergraduate final-year projects. Most of the students have outstanding records under my supervision. I have also served as the instructor of diverse courses, which covered both theory and engineering practice. Following is a list of my teaching experience.

- 2020, *Natural Language Processing*, Shenzhen University (Undergraduate Course, Instructor)
- 2020, *Natural Language Processing*, HKUST (Master's Course, Instructor)
- 2020, 2019, 2018, *Discrete Mathematics*, Shenzhen University (Undergraduate Course, Instructor)
- 2019, 2018, *Compilers*, Shenzhen University (Undergraduate Course, Instructor)
- 2018, *Programming Languages*, Shenzhen University (Undergraduate Course, Instructor)
- 2013, 2011, *Discrete Mathematics*, HKUST (Postgraduate Course, TA)
- 2012, 2009, *Principles of Programming*, HKUST (Undergraduate Course, TA)
- 2010, *Discrete Mathematics*, HKUST (Undergraduate Course, TA)

4.4 Teaching awards

I have received several teaching awards during the short three years of my faculty career in Shenzhen University.

- 2021 Outstanding Undergraduate Course Award, Shenzhen University
- 2020 Annual Excellence Award, Shenzhen University
- 2019 Best Course Award for *Discrete Mathematics*, CSSE, Shenzhen University
- 2019 Excellence Award in the "Torch" teaching program, Shenzhen University
- 2019 Best New Faculty Award, CSSE, Shenzhen University
- 2019 Second Price in the teaching competition, CSSE, Shenzhen University