Research Proposal

Doctoral Program in Systems and Information Engineering
Ph.D Computer Science

Title:
Question Answering Systems supported by Reinforcement and Machine Learning Methods

Name of Candidate: Happy Buzaaba

Abstract

The construction of Question Answering systems over unstructured and heterogeneous data sources requires the coordination of different Natural Language Processing (NLP) algorithms, data representation models and linguistic resources. The dynamic mapping from highly variable linguistic phenomena to the appropriate semantic interpretation method requires methods which are designed to cope with high semantic heterogeneity and complexity.

This project aims at building Question Answering system by developing a semantic parsing model which can be used for the interpretation of semantically heterogeneous data sources. The semantic parsing method will explore the fascinating intersection between explicit semantic representation models and machine/reinforcement learning models as well as the use of linguistic/data/distributional resources in the interpretation process.

Keywords
Question Answering systems, Natural Language Processing (NLP), Machine Learning, Reinforcement Learning, and Linguistic

Introduction

Web and social media have become primary sources of information. Users' expectations and information seeking activities co-evolve with the increasing sophistication of these resources. Beyond navigation, document retrieval, and simple factual question answering, users seek direct answers to complex and compositional questions. Such search sessions may require multiple iterations, critical assessment and synthesis [Marchionini, 2006].

The productivity of natural language yields a myriad of ways to formulate a question [Chomsky, 1965]. In the face of complex information needs, humans overcome uncertainty by reformulating questions, issuing multiple searches, and aggregating responses. Inspired by humans' ability to ask the right questions, the study will use Reinforcement Learning (RL) which has previously proved to perform at human level and can surpass human performance in games, which require reasoning Mnih, V et al 2015. RL is capable of performing complex reasoning in order to achieve a given goal. Deep neural networks, e.g., deep Q-learning can outperform humans on a number of games due to the ability to use past information Mnih, V et al 2016. Also according to Branavan et al 2009 RL is capable of learning from action based on read instructions.

This study will bring together Reinforcement learning and Machine learning (LSTM) to build a network that will hold prior information to generate the answer.

Related work

Deep learning uses multilevel data processing, which enables machines to understand complex patterns Weston, LeCun, Y et al 2015. This has prominently been used in NLP tasks. Yu et al 2014 use to match the answer sentence to a given question using deep learning. Furthermore, this avoids feature selection and linguistic data.

The use of deep learning has improved how the Question Answering (QA) task can be processed more efficiently. There has been a number of QA datasets released in the recent years. Weston, J et al 2015 introduced the challenging bAbI dataset, which holds 20 different types of QA tasks. In this work they show a baseline method using strongly supervised memory networks. They use Adaptive Memory Network combined with N-gram and non-linear matching function, which achieved 16 of the bAbI tasks. A Kumar, Irsory, O 2015 introduced DMN (Dynamic Memory Networks) which has achieved the current state-of-the-art results on bAbI. DMN identifies the question and tracks the answer through the content. X Guo, et al.,T Klinger, et al 2017 use an Reinforcement Learning (RL) based memory network to achieve the QA tasks.

B Bakker, et al 2002 shows that Reinforcement Learning (RL) and LSTM complement each other in T-maze tasks and pole balancing tasks. LSTM provides the memory in order to support RL and

supports the long path to the reward. This shows the capability to improve RL tasks using the memory of memory networks. Memory for the pole balancing and T-maze tasks supports the predictions by holding past information.
We believe that approaching Question Answering task with Reinforcement and machine learning techniques is academically challenge and practically interesting.

Reference:

Cambria, E.,White, B.: Jumping NLP curves: a review of natural language processing research [review article]. IEEE Computational Intelligence Magazine. 9(2), pp. 48-57 (2014).

Weston, J., Bordes, A., Chopra, S., Rush, A.M., van Merriënboer, B., Joulin, A., Mikolov, T.: Towards ai-complete question answering: A set of prerequisite toy tasks. arXiv preprint arXiv:1502.05698 (2015).

LeCun, Y., Bengio, Y., Hinton, G.: Deep learning. Nature. 521(7553), 436-444 (2015).

Kumar, A., Irsoy, O., Ondruska, P., Iyyer, M., Bradbury, J., Gulrajani, I., Zhong, V., Paulus, R., Socher, R.: Ask me anything: Dynamic memory networks for natural language processing. In: International Conference on Machine Learning, pp. 1378- 1387 (2016).

Sukhbaatar, S., Weston, J., Fergus, R.: End-to-end memory networks. In: Advances in neural information processing systems, pp. 2440-2448 (2015).

Bordes, A., Usunier, N., Chopra, S., Weston, J.: Large-scale simple question answering with memory networks. arXiv preprint arXiv:1506.02075 (2015).

Weston, J., Chopra, S., Bordes, A.: Memory networks. arXiv preprint arXiv:1410.3916 (2014).

Hochreiter, S.,Schmidhuber, J.: Long short-term memory. Neural computation. 9(8), 1735-1780 (1997).

Tan, M., Santos, C.d., Xiang, B., Zhou, B.: LSTM-based deep learning models for non-factoid answer selection. arXiv preprint arXiv:1511.04108 (2015).

Peng, B., Lu, Z., Li, H., Wong, K.-F.: Towards neural network-based reasoning. arXiv preprint arXiv: 1508.05508 (2015).

Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A.A., Veness, J., Bellemare, M.G., Graves, A., Riedmiller, M., Fidjeland, A.K., Ostrovski, G.: Human-level control through deep reinforcement learning. Nature. 518(7540), 529-533 (2015).

Mnih, V., Badia, A.P., Mirza, M., Graves, A., Lillicrap, T., Harley, T., Silver, D., Kavukcuoglu, K.: Asynchronous methods for deep reinforcement learning. In: International Conference on Machine Learning, pp. 1928-1937 (2016).

Branavan, S.R., Chen, H., Zettlemoyer, L.S., Barzilay, R.: Reinforcement learning for mapping instructions to actions. In: Proceedings of the Joint Conference of the 47th Annual Meeting of the ACL and the 4th International Joint Conference on Natural Language Processing of the AFNLP: Volume 1-Volume 1, pp. 82-90. Association for Computational Linguistics (2009).

Yu, L., Hermann, K.M., Blunsom, P., Pulman, S.: Deep learning for answer sentence selection. arXiv preprint arXiv:1412.1632 (2014).

Guo, X., Klinger, T., Rosenbaum, C., Bigus, J.P., Campbell, M., Kawas, B., Talamadupula, K., Tesauro, G., Singh, S.: Learning to Query, Reason, and Answer Questions On Ambiguous Texts. In: 5th International Conference on Learning Representations (2017).

Bakker, B.: Reinforcement Learning with Long Short-Term Memory. In: Neural Information Processing Systems (2002).

Cho, K., Van Merriënboer, B., Bahdanau, D., Bengio, Y.: On the properties of neural machine translation: Encoder-decoder approaches. arXiv preprint arXiv:1409.1259 (2014).