Emergence of Numerals in Multi-Agent Autonomous Communication System

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Abstract

This project aims to propose a new computational simulation method for the emergence of numerals based on multi-agent autonomous communication system following deep reinforcement learning methodology.

Acknowledgements

Any acknowledgements go here.

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Chapter 1

Introduction

Natural language processing (NLP) is an important and long-standing topic in artificial intelligence (AI), in which a core question is natural language understanding (NLU). With the rapid development of deep learning (DL), most current statae-of-the-art methods in NLP, e.g. [Socher et al., 2013, Mikolov et al., 2013, Kim, 2014], are based on DL models trained on massive static textual corpora. From an information processing perspective, the information flow of NLP-based human-computer interaction systems is illustrated in Figure 1.1 given as follow. As the diagram shows, the input of NLP systems are various kinds of textual materials generated by human beings to descibe their experiences/perceptions (E/P). Under such a perspective, symbols in natural languages are actually feature representations of the origianl E/P, whereas most current NLP systems directly take these symbols as original features.

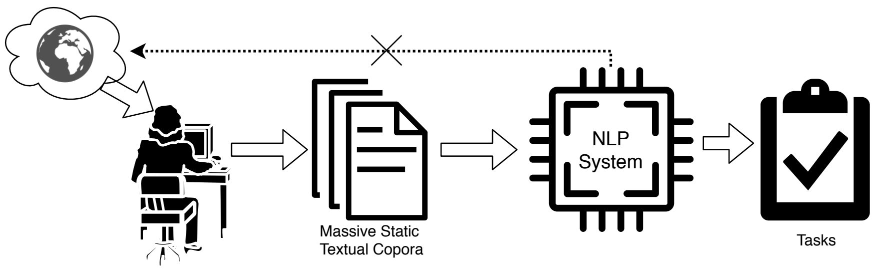

Figure 1.1: An overview of information flow in current NLP systems.

Considering the missing original E/P, grounded language learning (GLL) argues that models need a grounded environment to learn and understand language[Matuszek, 2018]. However, natural languages of the time have been developed for at least tens of thousands of years[Berwick and Chomsky, 2016] and already became very sophisticated. Thus, to verify that computational agents can truly ground symbols in natural languages to correspongding E/P and can complete the specified tasks, it is necessary to facillitate them to discover and develop various kinds of characteristics of natural language during autonomous communication of agents. There are already lots of works, e.g. [Hill et al., 2017, Havrylov and Titov, 2017, Yu et al., 2018, Kottur et al., 2017], aiming to facillitate the emergence of "natural language" in multi-agent autonomous communication systems. However, one significant limitation of previous works is that, only referential objects/attributes in environments, e.g. shapes and colors, were considered and to which discrete symbols were grounded to.

This project, on the other hand, aims to explore and analyse the grounding of abstractions which are non-referential in the original experiences/perceptions of human beings. However, as it is too huge a topic to tackle, our project is limited to cardinal numerals for the following reasons: i) numeral systems are relatively simple and self-contained[Hurford, 1999]; ii) concepts related to cardinal numerals are more straightforward to model with numeric representations; iii) functions of emergent cardinal numerals can be formalised and verified more reliably in simulation.

In this work, our main contributions are given as follows:

1. We are about the first to explore the problem of transmitting numerical concepts which corresponds to function words in natural languages in multi-agent autonomous communication system.

2. We transformed iterated learning proposed by [Smith et al., 2003] to train DL models and successfully facillitate computational agents to transmit numerical concepts.

3. We further analyse and discuss the compositionality of the emergent communication protocal and HERE!.

Chapter 2

Background

As we demonstrate in Chapter 1, there are 2 almost disjointly developed research topics that motivates this project, i.e. computer simulation methods in evolutionary linguistics and multi-agent games in GLL. Thus, in the following 2 sections, we will introduce works which are highly related to our project from these 2 different areas.

2.1 Computer Simulation Methods in Evolutionary Linguistics

The emergence and evolution of natural language have always been critical questions to the field of evolutionary linguistics [MacWhinney, 2013] and one important issue is to use quantitative methods to overcome the time limit on unpreserved pre-historic linguistic behaviors[Lieberman, 2006, Evans and Levinson, 2009]. Since it was first introduced by [Hurford, 1989], computer simulation methods have attracted a rapidly growing attention, e.g. [Hurford et al., 1998, Knight et al., 2000, Briscoe, 2002, Christiansen and Kirby, 2003, Bickerton and Szathmáry, 2009, Cangelosi and Parisi, 2012]. As we introduced in Chapter 1, one of our objectives is to facillitate computational agents to discover and develop various kinds of natural langauge phenonmana, which shares a same objective and motivation of computer simulation methods in evolutionary linguistics.

To imply and verify linguistics theories, there are 2 necessary component: i) environments, in which agents can execute actions and communicate with each other; ii) pre-defined elementary linguistic knowledge that can be manipulated and altered by agents. Further, we could categorise the environments into the following 3 different types according to their simulation objectives:

- *Iterated learning* introduced by [Kirby, 1999] which aims at simulating cultural transitions from generation to generation.
- *Language games* introduced by [Wittgenstein, 1953] which takes the emergent communication protocal in cooperation between individuals as a prototype of language.
- *Genetic evolution* introduced by [Briscoe, 1998] which aims at simluating evolution of languages as a kind of natural selection procedure[Darwin, 1859].

With environments and pre-defined elementary linguistic knowledge, computational agents can then learn bi-directional meaningutterance mapping functions[Gong and Shuai, 2013]. With diffrent kinds of resulting linguistic phenonmana, this simulation procedure can be broadly categorised intto 2 classes:

- lexical models, e.g. [Steels, 2005, Baronchelli et al., 2006, Puglisi et al., 2008], whose main concern is whether a common lexicon can form during the communication in agent community;
- syntactic and grammatical models, e.g. [Kirby, 1999, Vogt, 2005], in which agents mainly aim to map meanings (represented in various ways) to utterances (either structured or unstructured).

However, no matter how these mapping functions are learnt, e.g. by neural network models [Munroe and Cangelosi, 2002] or by mathematical equations [Minett and Wang, 2008, Ke et al., 2008], the most basic elements of linguistics, e.g. meanings to communicate about and a signalling channel to employ, are all pre-defined.

In contract, although we also follow the framework of language games and train agents in an iterated learning fashion, the basic linguistics elements in our project are not provided from the outset any more and computational agents can specify meanings of symbols/utterances by themselves.

2.2 Multi-agent Games in Grounded Language Learning

Unlike how we human beings learn and understand language, the current DL-based NLP techiniques learn semantics from only large-scaled static textual materials. Thus, GLL argues that computational also need to learn and understand languages by interacting with environments and grounding language into their E/P. With the recent rapid development of deep reinforcement learning (DRL), it is proven that computational agents can master a variaty of complex cognitive activities, e.g. [Mnih et al., 2015, Silver et al., 2017]]. Thus, a bunch of works in GLL apply DRL techiniques to facilitate agents to learn or invent natural languages[1], such as [Hermann et al., 2017, Mordatch and Abbeel, 2018, Havrylov and Titov, 2017, Hill et al., 2017].

To verify language abilities of computational agents, previous works in GLL usually follow the framework of language games, of which are mainly variants of referential games introduced by [Lewis, 1969], e.g. [Hermann et al., 2017, Havrylov and Titov, 2017]. Also, some works are more motivated by the competence instead of cooperation such as [Cao et al., 2018].

From another perspetive, based on the number of participated agents, we can broadly categorise language games in GLL into the following 2 types:

- *Single-agent games* usually need to be done by one agent and a human participator, in which the main concern is to explore how could computational agents learn the compositionality of semantics.

- *Multi-agent games* are usally completed by an agent population, in which the main concern is to explore how various kinds of natural language phenonmana emerge and envolve during communicating among agents.

However, like we mentioned in Chapter 1, whichever kind of langauge game they follow in previous works of GLL, the objects/attributes the symbols grounded to are all referential. We, on the other hand, aim to explore the feasibility of grounding symbols to non-referential objects (specifically, numerals) during the game.

[1] Strictly speaking, "invent natural language" should be called as "invent communication protocals sharing compoitionality like natural languages". However, as our project is to facilitate compositionality in multi-agent communication protocals, we thus call these emergent communication protocals a kind of "langauge" invented by agents

Chapter 3

Set Generation Game and Models

3.1 Game Description

One hypothesis of our work is that, the linguistic hypotheses can by implied by game dynamics.

3.1.1 Game Procedure

3.1.2 Numerals in the Game

3.2 Proposed Models

3.2.1 Set2Seq2Seq Models

3.2.2 Numeral Iterated Learning

3.2.3 Baseline Models

Chapter 4

Experiment Results and Analysis

Chapter 5

Conclusions

5.1 Final Reminder

The body of your dissertation, before the references and any appendices, *must* finish by page 40. The introduction, after preliminary material, should have started on page 1.

You may not change the dissertation format (e.g., reduce the font size, change the margins, or reduce the line spacing from the default 1.5 spacing). Over length or incorrectly-formatted dissertations will not be accepted and you would have to modify your dissertation and resubmit. You cannot assume we will check your submission before the final deadline and if it requires resubmission after the deadline to conform to the page and style requirements you will be subject to the usual late penalties based on your final submission time.

5.2 Further Discussion

Bibliography

[Baronchelli et al., 2006] Baronchelli, A., Felici, M., Loreto, V., Caglioti, E., and Steels, L. (2006). Sharp transition towards shared vocabularies in multi-agent systems. *Journal of Statistical Mechanics: Theory and Experiment*, 2006(06):P06014.

[Berwick and Chomsky, 2016] Berwick, R. C. and Chomsky, N. (2016). *Why only us: Language and evolution*. MIT press.

[Bickerton and Szathmáry, 2009] Bickerton, D. and Szathmáry, E. (2009). *Biological foundations and origin of syntax*, volume 3. Mit Press.

[Briscoe, 1998] Briscoe, E. J. (1998). Language as a complex adaptive system: co-evolution of language and of the language acquisition device. In *Proceedings of eighth computational linguistics in the Netherlands Conference*, pages 3–40. Citeseer.

[Briscoe, 2002] Briscoe, T. (2002). *Linguistic Evolution through Language Acquisition: Formal and Computational Models*. Cambridge University Press.

[Cangelosi and Parisi, 2012] Cangelosi, A. and Parisi, D. (2012). *Simulating the evolution of language*. Springer Science & Business Media.

[Cao et al., 2018] Cao, K., Lazaridou, A., Lanctot, M., Leibo, J. Z., Tuyls, K., and Clark, S. (2018). Emergent communication through negotiation. *arXiv preprint arXiv:1804.03980*.

[Christiansen and Kirby, 2003] Christiansen, M. H. and Kirby, S. (2003). *Language evolution*. OUP Oxford.

[Darwin, 1859] Darwin, C. (1859). On the origin of species by means of natural selection (j. murray, london).

[Evans and Levinson, 2009] Evans, N. and Levinson, S. C. (2009). The myth of language universals: Language diversity and its importance for cognitive science. *Behavioral and brain sciences*, 32(5):429–448.

[Gong and Shuai, 2013] Gong, T. and Shuai, L. (2013). Computer simulation as a scientific approach in evolutionary linguistics. *Language Sciences*, 40:12–23.

[Havrylov and Titov, 2017] Havrylov, S. and Titov, I. (2017). Emergence of language with multi-agent games: Learning to communicate with sequences of symbols. In *Advances in neural information processing systems*, pages 2149–2159.

[Hermann et al., 2017] Hermann, K. M., Hill, F., Green, S., Wang, F., Faulkner, R., Soyer, H., Szepesvari, D., Czarnecki, W. M., Jaderberg, M., Teplyashin, D., et al. (2017). Grounded language learning in a simulated 3d world. *arXiv preprint arXiv:1706.06551*.

[Hill et al., 2017] Hill, F., Hermann, K. M., Blunsom, P., and Clark, S. (2017). Understanding grounded language learning agents. *arXiv preprint arXiv:1710.09867*.

[Hurford, 1989] Hurford, J. R. (1989). Biological evolution of the saussurean sign as a component of the language acquisition device. *Lingua*, 77(2):187–222.

[Hurford, 1999] Hurford, J. R. (1999). Artificially growing a numeral system. `http://www.lel.ed.ac.uk/~jim/grownum.html`. Accessed March 12, 2019.

[Hurford et al., 1998] Hurford, J. R., Studdert-Kennedy, M., and Knight, C. (1998). *Approaches to the evolution of language: Social and cognitive bases*. Cambridge University Press.

[Ke et al., 2008] Ke, J., Gong, T., and Wang, W. S. (2008). Language change and social networks. *Communications in Computational Physics*, 3(4):935–949.

[Kim, 2014] Kim, Y. (2014). Convolutional neural networks for sentence classification. *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing*.

[Kirby, 1999] Kirby, S. (1999). *Function, selection, and innateness: The emergence of language universals*. OUP Oxford.

[Knight et al., 2000] Knight, C., Studdert-Kennedy, M., and Hurford, J. (2000). *The evolutionary emergence of language: social function and the origins of linguistic form*. Cambridge University Press.

[Kottur et al., 2017] Kottur, S., Moura, J. M., Lee, S., and Batra, D. (2017). Natural language does not emerge'naturally'in multi-agent dialog. *arXiv preprint arXiv:1706.08502*.

[Lewis, 1969] Lewis, D. (1969). *Convention: A philosophical study*. John Wiley & Sons.

[Lieberman, 2006] Lieberman, P. (2006). *Toward an evolutionary biology of language*. Harvard University Press.

[MacWhinney, 2013] MacWhinney, B. (2013). *The emergence of language*. Psychology Press.

[Matuszek, 2018] Matuszek, C. (2018). Grounded language learning: Where robotics and nlp meet. In *IJCAI*, pages 5687–5691.

[Mikolov et al., 2013] Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., and Dean, J. (2013). Distributed representations of words and phrases and their compositionality. In Burges, C. J. C., Bottou, L., Welling, M., Ghahramani, Z., and Weinberger, K. Q., editors, *Advances in Neural Information Processing Systems 26*, pages 3111–3119. Curran Associates, Inc.

[Minett and Wang, 2008] Minett, J. W. and Wang, W. S. (2008). Modelling endangered languages: The effects of bilingualism and social structure. *Lingua*, 118(1):19–45.

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

[Mordatch and Abbeel, 2018] Mordatch, I. and Abbeel, P. (2018). Emergence of grounded compositional language in multi-agent populations. In *Thirty-Second AAAI Conference on Artificial Intelligence*.

[Munroe and Cangelosi, 2002] Munroe, S. and Cangelosi, A. (2002). Learning and the evolution of language: The role of cultural variation and learning costs in the baldwin effect. *Artificial life*, 8(4):311–339.

[Puglisi et al., 2008] Puglisi, A., Baronchelli, A., and Loreto, V. (2008). Cultural route to the emergence of linguistic categories. *Proceedings of the National Academy of Sciences*, 105(23):7936–7940.

[Silver et al., 2017] Silver, D., Schrittwieser, J., Simonyan, K., Antonoglou, I., Huang, A., Guez, A., Hubert, T., Baker, L., Lai, M., Bolton, A., et al. (2017). Mastering the game of go without human knowledge. *Nature*, 550(7676):354.

[Smith et al., 2003] Smith, K., Kirby, S., and Brighton, H. (2003). Iterated learning: A framework for the emergence of language. *Artificial life*, 9(4):371–386.

[Socher et al., 2013] Socher, R., Perelygin, A., Wu, J., Chuang, J., Manning, C. D., Ng, A., and Potts, C. (2013). Recursive deep models for semantic compositionality over a sentiment treebank. In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*, pages 1631–1642, Seattle, Washington, USA. Association for Computational Linguistics.

[Steels, 2005] Steels, L. (2005). The emergence and evolution of linguistic structure: from lexical to grammatical communication systems. *Connection science*, 17(3-4):213–230.

[Vogt, 2005] Vogt, P. (2005). On the acquisition and evolution of compositional languages: Sparse input and the productive creativity of children. *Adaptive Behavior*, 13(4):325–346.

[Wittgenstein, 1953] Wittgenstein, L. (1953). *Philosophical investigations*. John Wiley & Sons.

[Yu et al., 2018] Yu, H., Zhang, H., and Xu, W. (2018). Interactive grounded language acquisition and generalization in a 2d world. *arXiv preprint arXiv:1802.01433*.

Appendices