Exploring characterization capacity of agents for composable symbolic language

**Abstract**

Recent advances on symbolic language in neural network based multi-agent systems have shown great progress in compositionality, which is taken as one of the main feature distinguishing human language from animal language. However, these efforts only explored environmental pressures, without realizing the importance of the characterization capacity of agents.

In this work, we explore the relationship between the characterization capacity of agents and the compositionality of symbolic languages. By both proving with mutual information theory and verifying with extensive experiments, we made the counter-intuitive conclusion that symbolic languages with higher compositionality require lower characterization capacity of agents and are easier-to-teach.

**Introduction**

The emergence and evolution of human language has always been an important and controversial issue. The problem covers many fields, including artificial intelligence in computer science. Computer scientists induce the emergence and evolution of languages in multi-agent systems by setting up pure communication scenarios, such as referential games and communication-action policies.

Researchers have confirmed that agents can master a symbolic language to complete appointed tasks. Such symbolic language is a communication protocol using symbols or characters to represent concepts. Moreover, people not only care about the emergence of language, but also try to make the emergent language similar to human natural language.

Compositionality is a widely accepted metric used to measure the hierarchical complexity of language structure, and it is also a key feature to distinguish human language from animal language. Syntactic languages with high compositionality, such as human natural language, are able to express complex meanings through the combination of symbols and to produce certain syntax. In contrast, non-syntactic languages with low compositionality, such as animal languages, are almost impossible to extract specific concepts from a single symbol. Researchers have recognized the importance of compositionality and found that various environmental pressures would affect compositionality.

Besides environmental pressures, we suggest that the impact of internal factors from agents themselves on compositionality is equally significant. A biological hypothesis show that the cranial capacity of animals is not big enough to master languages with high compositionality. In neuron network based multi-agent systems, this hypothesis corresponds to a point of view that it’s difficult for agents with insufficient characterization capacity (i.e. number of neural nodes) to master languages with high compositionality. However, combine theoretical analysis and environmental results, we hold the complete opposite view -- within the range afforded by the need for successful communication, lower characterization capacity facilitates the emergence of symbolic language with higher compositionality.

For theoretical analysis, we use the MSC (Markov Series Channel) to model language transmission process and the probability distribution of symbols and concepts to model agents. Our methodology has the certain generalization ability cause it does not depend on the specific structure or algorithm of agents’ model. Combine the MSC model with mutual information theory, we certify the characterization capacity’s impact on compositionality theoretically. Specifically, we prove that a symbol of emergent languages with lower compositionality need carry more complex semantic information (i.e. mutual information between original concepts received by speaker and predicted concepts outputted by listener). So agents use such languages require more neural nodes in to characterize the semantic information.

In terms of experiments, in order to examine the relationship between capacity and compostionality in 'natural' environments, we avoid imposing any environmental pressures on agents through the following settings: a). Scenarios: a listener-speaker referential games for pure communication; b). Models: the listener and the speaker don’t share any parameters, and are not connected together to form an *Auto-Encoder* structure; c). Rewards: the only criterion for each of agents to receive a positive reward is whether the forecast output from the listener is correct. Under an experimental framework with such settings, the experimental results show that the effect of characterization capacity on compositionality is consistent with the theoretical analysis.

In addition, as a by-product of theoretical analysis, we propose ‘bilateral’ metrics for measuring compositionality and the degree of alignment between symbols and concepts. For the degree of alignment between symbols and concepts, the metric should be higher only if speaker and listener ‘bilateral’ correspond a symbol to the same concept more stably. For compositionality, we hold the view that a single symbol of symbolic languages with higher composionality should be used to ground or transmit a certain concept ‘bilaterally’ and more exclusively between listener and speaker.

To sum up, our contributions are as follows：

a). We explore a novel factor (i.e. characterization capacity of agents) in compositionality, and show its impact both theoretically and experimentally.

b). We offer a methodology with the certain generalization ability to [quantificationally](C:/Users/haoyi/AppData/Local/youdao/dict/Application/8.9.4.0/resultui/html/index.html#/javascript:;) analyze the process of language transmission.

c). We propose novel ‘bilateral’ metrics for measuring communication.

Para 1: Compositionality is important to symbolic language. Recent works have made greate progress.

Para 2: However, previous works focus on environmental pressue, without realizing the importance of characterization of agents

Para 3: Different from previous works, we found that xxxxx

Para 4: In this paper, we explored xxxx

Para 5:

**Related work**

一些工作是基于某个启发式的猜想，提出某个environmental pressure对compositionality的影响。XXX提出了small vocabulary sizes；XXX提出了memoryless；XXX提出了carefully constructed distractors；XXX提出了frequently reset。他们不但都忽略了一个源于模型本身的重要影响因素characterization capacity，而且缺少理论支撑。

不仅如此，’naturally’ emergent communication也是一个值得关注的问题。部分工作中使用了精心构造的scenarios, models, reward, loss function。XXX使用了XXX...。这些做法实质上等同于对agents施加了额外的人为诱导，不仅削弱了’naturally emergent compostional language’的相关结论，而且也分散/模糊/稀释了单个因素对compositionality的影响。

此外，关于metrics to measure communication的争议也从未停止。许多工作都提出了关于度量compositionality and the degree of alignment between symbols and concepts的metrics。*On the Pitfalls of Measuring Emergent Communication*这篇文章整理了近年来出现的widely accepted metrics，并将它们分为两类：those that measure *positive signaling*, 这类metrics是站在speaker的视角，用于衡量speaker说出的symbols和接收的concepts之间关系，例如XXX; and those that measure *positive listening*, 这类metrics是站在listener的视角，用于衡量listener收到的symbols和预测的concepts之间的关系，例如XXX。总的来说，这些metrics全都是’[unilateral](C:/Users/haoyi/AppData/Local/youdao/dict/Application/8.9.4.0/resultui/html/index.html#/javascript:;) ’ metrics，但它们都缺少一个非常重要的’bilateral’特征：speaker和listener的相互理解程度，i.e.在concepts和symbols的对应上的一致性。

综上，这些工作都无法回答这样一个问题：在’natural’环境中，模型的characterization capacity对compositionality of emergent language有怎样的影响？这也是这篇文章要解决的问题。我们结合理论分析以及实验结果，并建立一种更合理的’bilateral’ metrics，so that we can [quantificationally](C:/Users/haoyi/AppData/Local/youdao/dict/Application/8.9.4.0/resultui/html/index.html#/javascript:;) measure characterization capacity’s impact on compositionality of emergent language。

**Experimental Framework**

*#In this section, we introduce a referential game platform and our listener-speaker RNN model.*

*#subsection1: Game set up*

*#subsection2: Agent architecture*

*#subsection3: Training Algorithm*

*#subsection4: Evaluation*

**Compositionality and Characterization Capacity**

*#We get an counter-intuitive observation on the relationship between the compositionality and the number of nodes in the hidden layer.*

*#We get an natural infer: symbolic languages with higher compositionality require lower characterization capacity (i.e. less nodes in the hidden layer).*

**Theoretical Analysis**

*#In this section, we prove the infer above mentioned theoretically on the basis of mutual information theory.*

**Experiments**

**Discussion**