Revisiting the Natural Emergence of Language with Agent Capacity

**Abstract**

The natural emergence of symbolic languages with high compositionality has

attracted extensive attentions from a broad range of communities. Existing

studies achieve high compositionality through \emph{deliberately handcrafted}

inductions (e.g., small vocabulary sizes, carefully constructed distractors,

and ease-of-teaching) in multi-agent learning, which are unnatural.

Yet, few studies investigate the emergence of symbolic language with high compositionality in

\emph{``natural''} environments, i.e., without any deliberately handcrafted

inductions.

In this paper, we are the first to successfully achieve high compositional symbolic

language in a purely \emph{natural} environment.

Initially, by thoroughly investigating the compositionality of symbolic

language emerged after removing the \emph{deliberately handcrafted}

inductions, we observe that the agent capacity plays the key role in

compositionality. We further reveal and characterize the quantitative relationship

between the agent capacity and the compositionality of symbolic language both

theoretically and experimentally. The theoretical analysis is built on the MSC

(Markov Series Channel) model for the language transmission process and a

novel mutual information-based metric for the compositionality. The

experiments are conducted on a listener-speaker referential game framework

with eliminated external environment factors. Both theoretical analysis and

experimental results lead to a counter-intuitive conclusion that lower agent

capacity facilitates the emergence of symbolic language with higher

compositionality. Based on our conclusion, we are able to generate higher

compositional symbolic language with a high probability.

**Introduction**

The emergence of human language has always been an important and controversial issue. This problem attracts attentions from a broad range of communities, including XX and computer science. In computer science, 研究自然语言产生的主要技术手段是什么？从而引出发生语言。

The emergence of human language has always been an important and controversial issue. This problem attracts attentions from a broad range of communities, including [philology](C:/Users/haoyi/AppData/Local/youdao/dict/Application/8.9.4.0/resultui/html/index.html" \l "/javascript:;), [biology](C:/Users/haoyi/AppData/Local/youdao/dict/Application/8.9.4.0/resultui/html/index.html" \l "/javascript:;) and computer science. In computer science, researchers induce and analyze the emergent language in multi-agent systems by setting up communication scenarios, such as referential games and communication-action policies.

Compositionality is a widely used metric to evaluate the emergent language XXX.第一句话：发生语言的重要度量指标是compositionality（从而接上一段）。Compositionality的严格定义是什么。举两个例子进一步形象地解释说明Compositionality是什么。

Compositionality is a widely used metric to evaluate the emergent language. It is a concept in the [philosophy of language](https://iep.utm.edu/lang-phi/) [1], which describes and quantifies how complex expressions can be assembled out of simpler parts [2]. For example, Figure1(a) shows a perfect compositional language (with maximum compostionality). In this example, each shape is represented by a unique value of symbol s\_0 and each color is represented by symbol s\_1. Figure1(b) shows a language with low compostionality. Colors and shapes are ambiguous if only we extract information from a single symbol.

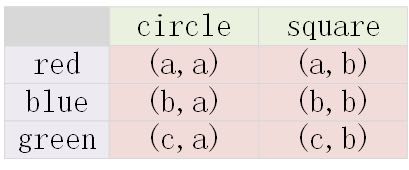
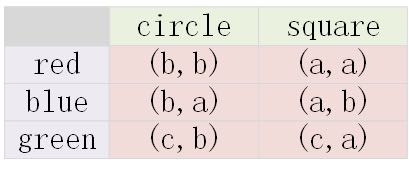
 

Figure1. (a): The correspondence between symbol sequences (s\_0, s\_1) and (shape, color) pairs in a perfectly compostional language. s\_0, s\_1 in {a, b, c}, shape in {circle, square} and color in {red, blue, green}; (b): The correspondence between symbol sequences (s\_0, s\_1) and (shape, color) pairs in a language with low compostionality.

[1].[https://iep.utm.edu/composit/#H1](https://iep.utm.edu/composit/" \l "H1)

[2].<https://golem.ph.utexas.edu/category/2019/12/compositionality_first_issue.html>

Prior studies focus on investigating how to affect the compositionality of XXX。现有工作重点研究影响compositionality的关键因素。例如，XX，XX，和XX。这些工作无一例外都只考虑了外部环境因素，同时这些环境因素在实际的场景中可能太严格了，可能不存在。

Prior studies focus on investigating how to affect the compositionality of the emergent language. Researchers have found that various environmental pressures would affect compositionality, e.g., small vocabulary sizes[3], memoryless[4], carefully constructed rewards[5] and ease-of-teaching[6]. However, these works only consider \emph{nurture} [7] (i.e., environmental factors), rather than \emph{nature} (i.e., hereditary factors from agents), when inducing or exploring the emergent language without exception. Moreover, some environmental pressures, like regrading the entropy as an item of additional rewards, may be too ideal to exist in the real world.

[3].

[4].

[5].

[6].

[7].<https://www.verywellmind.com/what-is-nature-versus-nurture-2795392>

In contrast to prior work, we investigate the compositionality/emergent language from a new perspective, i.e., the internal agent capacity XXX. 和之前的工作仅考虑外部环境因素不同，我们第一次发现了内部capacity对compositionality的影响。具体来说，我们首先发现了当前compositionality度量的XXX缺点，提出了新的bilateral度量。在此基础上我们从理论和实验两方面验证了agent capacity和compositionality之间的关系。

In contrast to prior work, we investigate the compositionality of emergent language from a new perspective, i.e., the agent capacity. Different from previous work that only considers external environmental factors, we study the impact of agent internal capacity on the compositionality of emergent language. Specifically, we first analyze the correlation between agent capacity and compositionality theoretically, and propose a novel metric to evaluate compostionality quantitatively. Then, on the basis of the theoretical analysis and the metric proposed, we verify the relationship between agent capacity and compostionality experimentally.

Theoretically, XXX。理论上，XXX（一句话说明用了什么方法，如何证明的）。具体来说，XXX（详细解释用到的方法和过程）。最终得到的结论是XXX。

Theoretically, on the basis of mutual information theory[8], we analyse the correlation between compostionality of the emergent language and complexity of the semantic information carried by a symbol. Such semantic information can be characterized in neural network-based agents and requires the certain capacity (i.e., the count of neural nodes in the hidden layer). Specifically, we use the MSC (Markov Series Channel)[9] to model the language transmission process and use the probability distribution of symbols and concepts to model policies of agents. After modelling, we use the mutual information matrix MRI^B to quantitatively represent the semantic information, and each column of MRI^B correspond to information carried by one symbol. We find that each column of the matrix should be an one-hot vector for a perfectly compositional language, cause a symbol only transmit information of a certain concept exclusively. Therefore, the average similarity between the columns of MRI^B and a one-hot vector is higher, indicating that the emergent language is more compostional (i.e., the compostionality is higher). We propose the metric \emph{MIS} to measure compositionality by calculating such average similarity quantitatively. Different from other metrics, such as \emph{topographic similarity}[10] and \emph{posdis}[11], \emph{MIS} is a bilateral metric because it takes both listener and speaker's understanding of semantics into account. Moreover, \emph{MIS} comes lower indicates that the emergent language tends to delivery semantic information about more concepts in each symbol, so that the complexity of semantic information carried by one symbol tend to be higher. As a result, higher agent capacity is required to characterize the more complex semantic information when \emph{MIS} (i.e., compositionality) is lower.

[8].

[9].

[10].

[11].

Experimentally, XXX。实验上，通过XXX框架从两个方面验证了capacity和compositionality的关系。这个框架的特点是什么。第一个实验是XXX。第二个实验是XXX。最终得到的结论是XXX。

Experimentally, we verify the relationship between agent capacity and compostionality. We build a listener-speaker referential game as experimental framework, and train agents of Stochastic Policy Gradient Algorithm[12] with the correctness of forecast output from the listener as the criterion (i.e., reward). The criterion does not imply any environmental pressures on the agents. Therefore, we can study the impact of capacity on the compositionality without any environmental pressures’ affection. Moreover, to study the impact of capacity on the compositionality under a more ‘natural’ environment, the speaker and listener are disconnected models without sharing parameters. Our first experiment is to verify that agent need higher capacity to master an artificial language with lower compositionality under a scenario of language teaching. Specifically, we fabricate the speaker to output preassigned languages with different compostionality respectively, and train the listener to interpret the preassigned language. For all artificial language, we compare the accuracy curve during training process of the listener with different capacity, and show how capacity affect learning languages with different compostionality. Our second experiment is to verify that lower agent capacity would facilitate higher compostionality of the emergent language under a scenario of language inducing. Specifically, we training a speaker and a listener to create a communication protocol (i.e., emergent language), so that the listener can select the same object which is received by the speaker. By adjusting capacity and comparing the compositionality of emergent language, we show that the emergent language attend to have higher compositionality when agent capacity is restricted more stringently. As a result, these two experiments verify the negative correlation between agent capacity and compostionality both in language teaching and language inducing.

[12].

This paper makes the following contributions:

1. 提出了新的度量compositionality的标准，和之前的度量相比考虑了XXX，which is common in real world communication；
2. 理论上证明了capacity和compositionality的关系；
3. 实验上验证了无论是teaching还是natural emergent的方式，两者都是有关系的。

This paper makes the following contributions:

We propose a ‘bilateral’ metric \emph{MIS}, which takes both listener and speaker's understanding of semantics into account. Compare to previous ‘unilateral’ metrics, \emph{MIS} can handle situations where the semantics of the listener and the speaker are not exactly the same (, we discuss the problem in next section).

We analyse the relationship between compostionality and agent capacity theoretically.

We verify the negative correlation between agent capacity and compostionality both in language teaching and language inducing.

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.

废话太多，简单强调发生语言很重要即可，可引用乔姆斯基XXX。

people try to make the emergent language similar to human natural language. XXX用了XXX方法做了XXX致力于让机器语言接近人类语言。（引用其他语言学相关工作，尤其是AAAI上的）

一个重要的引用：Barbara Partee 2004 提出的compostionality。

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 concepts 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 (i.e. attributes of objects) from a single symbol.

这段废话也多，只需要强调High compositionality的语言的两个特征：

1. Syntax
2. 一个symbol对应一个concept

但是low compostionality的语言没有这两个特征

Researchers have found that various environmental pressures would affect compositionality. e.g. small vocabulary sizes, memoryless, carefully constructed distractors, ease-of-teaching。

但是，他们都是研究环境对compotionality的影响。我们发现了模型本身也对compostionality有影响。

Besides environmental pressures, we suggest that the impact of internal factors from agents themselves on compositionality is equally significant.

Many people believe 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. 废话太多，应一句写完，长度不超过下面的however后面。

However, we found that lower characterization capacity facilitates the emergence of symbolic language with higher compositionality, within the range afforded by the need for successful communication. We prove the point with mutual information theory and experiments.

From theoretical analysis, we define \emph{bilaterality} as the quantitative metrics for compositionality. The bilaterality is the similarity between an identity matrix and the mutual information matrix of concepts and symbols (after normalization). We use the MSC (Markov Series Channel) to model the language transmission process and use the probability distribution of symbols and concepts to model policies of agents. Combining the MSC model with mutual information theory, we prove that the emerging language with lower bilaterality tends to delivery information about more concepts in each symbol. .这句话感觉不太符合表意，而且复杂度并不是指互信息的。理论证明的是“互信息矩阵与单位矩阵的相似度越低，表示单个symbol 越倾向于分散传递更多concepts的信息 (i.e. compostionality / bilaterality越低)”。后面理论分析部分得到结论的过程是“互信息矩阵与单位矩阵的相似度越低，表示单个symbol 越倾向于分散传递更多concepts的信息 (i.e. compostionality越低)，(从这里开始就不严谨了) 从而单个symbol携带的语义信息的复杂度越高，最终导致agents表征单个symbol中的语义信息需要的capacity越大。”

Then with experiments we show that a low-bilateral (i.e. low-compositionality) language needs higher capacity of the model to emerge. We build a listener-speaker referential game as experimental framework, and train agents with the correctness of forecast output from the listener as the only criterion. (The criterion does not imply any environmental pressures on the agents)这句的描述还是不太准确，体现“不包含任何environmental pressures”的不是correctness这个criterion本身，而是我们**仅仅使用**correctness训练agents. Therefore, we can study the impact of capacity on the compositionality without any environmental pressures’ affection (因为前面还在提environmental pressures，这里突然没了有点突兀，所以感觉是不是加个后缀算是给environmental pressures收个尾). Moreover, to study the impact of capacity on the compositionality under a more ‘natural’ environment, the speaker and listener are individual agents, i.e. disconnected models without sharing parameters (想给individual的定义加上一个“模型不相连”，这一点还是比较重要的，如果允许相连就是个auto-encoder了，auto-encoder里的编码不能称作emergent language). The conclusion suggests that by restricting the number of neurons in a model the emerging languages attend to have higher bilaterality, thus higher compositionality.

To sum up, our contributions are as follows：

a). We propose a novel metric, namely \emph{bilaterality}, to quantitatively measure the compositionality of the emerging language.

b). With experiments we found that the capacity of model is anti-correlated with the bilaterality, showing that restricting the number of neurons in a model attends to emerging a language with higher compositionality.

**Related work**

许多工作在environment with handcraft induction中研究compositionality of emergent language.

此外，关于metrics to measure communication的争议也从未停止。

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ease-of-teaching。他们都忽略了一个源于模型本身的重要影响因素capacity。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" \l "/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" \l "/javascript:;) measure capacity’s impact on compositionality of emergent language。

**Experimental Framework**

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

我们在referential game中搭建实验框架。referential game是一种speaker和listener通过交流达成合作的场景。许多工作，例如XXX，都使用referential game研究emergent language。下面，我们分别介绍实验的set up，agent的模型结构，训练算法，和评估方法。

In this section, a referential game platform and a speaker-listener model are introduced. Referential game is commonly used in the emergent language study, such as [][]. In this game, the speaker needs communicate with the listener to complete a task cooperatively. The game setup for the referential game is firstly described. Then, how to construct the speaker-listener with the neural networks is introduced. Lastly, the training algorithm and the evaluation methods are discussed.

*#subsection1: Set up*

在我们使用的referential game中，每次游戏都遵守如下基础规则：

a). speaker agent S根据input object t输出symbol sequence s；

b). listener agent L根据symbol sequence s输出predict result t^；

c). 当t = t^时，认为agents在本次游戏成功，S和L分别获得reward R(t, ) = 1；否则，agents失败，并分别获得reward R(t, ) = -1

object t由固定长度的concept sequence (c\_0, c\_1)组成，记为t = (c\_0, c\_1)。其中concept c\_0 (shape)和c\_1 (color)分别有自己的取值集合M\_0和M\_1。实验中，we let |M\_i| (i = 0,1) range from 3 to 8 。我们用长度为|M\_0|的one-hot vector表示shape c\_0，用长度为|M\_1|的one-hot vector表示color c\_1。这两个one-hot vector concatenate成一个长度为|M\_0|+|M\_1|的vector，t由该vector表示。

s是固定长度的symbol sequence (s\_0, s\_1)。其中每个symbol s\_i (i=0,1)的取值都属于vocabulary set V。实验中，we let |V| range from 3 to 10，并且保证|V|^2 >= |M\_0|\*|M\_0|，即保证symbol sequence (s\_0, s\_1)足够分别描述所有情况的object t。我们用两个长度为|V|的one-hot vector分别表示s\_0和s\_1。这两个one-hot vector concatenate成一个长度为2 \* |V|的vector，s由该vector表示。

predict result 由一个长度为|M\_0|\*|M\_1|的one-hot vector表示。该one-hot vector中的每个bit对应一个object，即一个shape和color的组合，记为 = (, )。具体地，[i \* |M1| + j] = 1 correspond to [i] = 1 & [j] = 1 (i = 0, ..., |M0| - 1; j = 0, ..., |M1| - 1)。

我们定义的 = t是指t和分别对应的object相同，i.e.对应的(c0, c1) = (, )。

In the referential game, the agents should obey the following rules:

1. The speaker agent S uses the input object t to output the corresponding symbol sequence s;
2. The listener agent L uses the symbol sequence s to output the predict result $\hat{t}$;
3. If $t=\hat{t}$, this game is successful, and each agent receives reward $R(t,\hat{t}=1$; otherwise, the game is failed, and the reward is set as $R(t,\hat{t}=-1$.

An input object t is a concept sequence with fixed length, denoted $t=(c\_0,c\_1)$. The concept $c\_0(shape)$ and $c\_1(color)$ are indicated as a one-hot vector respectively. The length of each one-hot vector ranges from 3 to 6. These two vectors are concatenated to denote the input object t.

Each symbol sequence s contains two words, denoted $(s\_0,s\_1)$. Each word $s\_i$ is chosen in the vocabulary set $V$. In this game, let the card $|V|$ range from 4 to 10, and the inequation $|V|^2\geq|M\_1||M\_1|$ is satisfied to ensure the symbol sequence $(s\_0,s\_1)$ can be used to denote all the input object t. The one-hot vector with the length $|V|$ is used to indicate the word $s\_0$ and $s\_1$ respectively. Then, the two one-hot vectors are concatenated to denote the symbol sequence s.

The predict result $\hat{t}$ is denoted as a one-hot vector with the length $|M\_0||M\_1|$. Each bit of the one-hot vector denotes one input object. If the predict result $\hat{t}[i\*|M\_1|+j]=1$, the one-hot vector of each predict concept $\hat{c}\_0$ and $\hat{c}\_1$ respectively satisfied $\hat\_{c}\_0[i]=1$ and $\hat{c}\_1[j]=1$.

If $(c\_0,c\_1) is equal to $(\hat{c}\_0,\hat{c}\_1)$, the input object and the predict result indicate the same object.

*#subsection2: Agent architecture*

Agents以各自强化学习的策略进行上述referential game。将speaker agent S和listener agent L的policy分别记为pi\_S和pi\_L。pi\_S表示给定输入object t，speaker输出symbol s\_0和s\_1的条件概率P(s\_0|t)和P(s\_1|t)。speaker S分别根据概率分布P(s\_0| t)和P(s\_1|t)随机采样输出s\_0和s\_1。pi\_L表示给定输入symbol sequence s = (s\_0, s\_1)，listener输出predict result 的条件概率P( | s\_0, s\_1)。listener L根据概率分布P( | s\_0, s\_1)随机采样输出。Agents分别用一个神经网络连接各自的policy的输入和输出。模型的architecture如figure1所示。

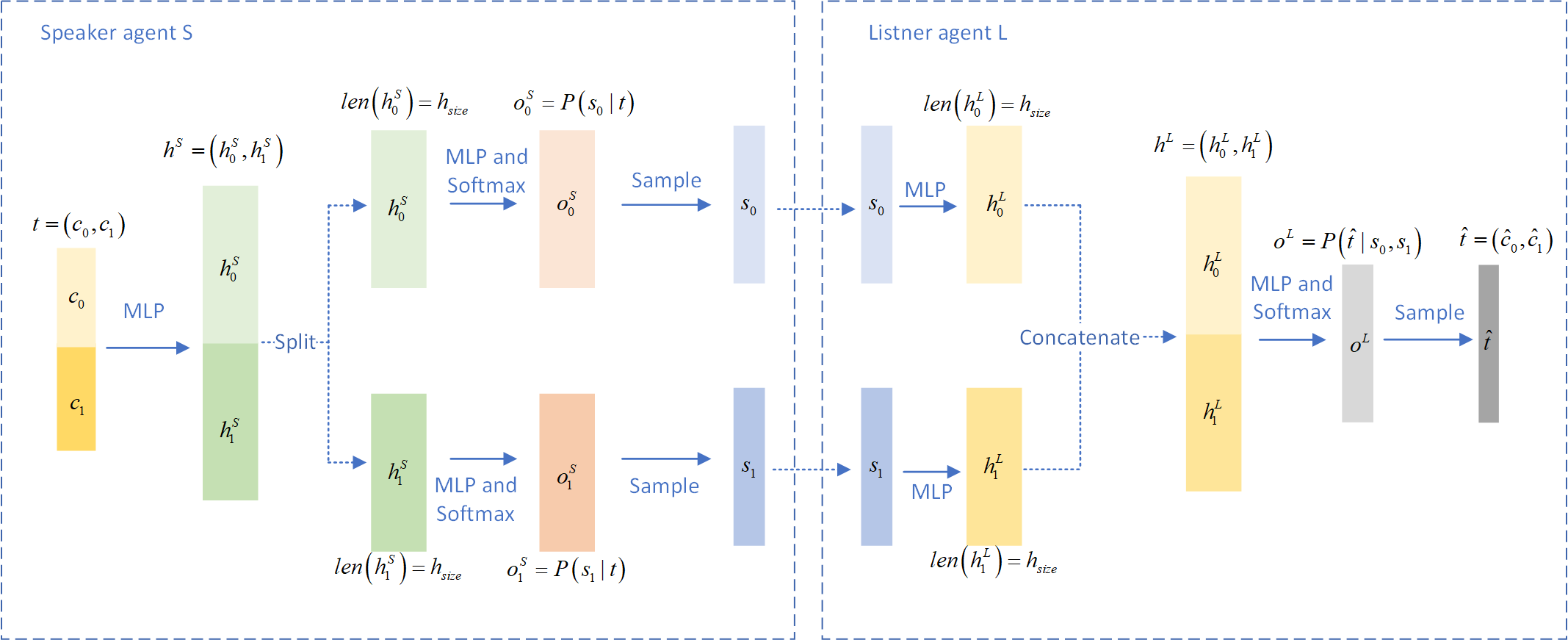


Figure1. the architecture of agents

对于speaker的神经网络模型，输入t经过一个全连接层并激活得到hidden layer h^S，h^S的神经元节点数为h\_size \* 2。Splitting h^S equally得到两个长度为h\_size的neural vectors h^S\_0和h^S\_1。h^S\_i (i=0,1)各自依次经过一个全连接层和一个softmax得到output layer o^S\_i。o^S\_i (i=0,1)是一个长度为|V|的vector，其每个分量表示，给定输入t时，s\_i的每个取值的概率，即P(si| t)。

对于listener的神经网络模型，输入的symbol sequence s = (s\_0, s\_1)中，s\_i (i=0,1)各自经过一个全连接层并激活得到hidden layer h^L\_i，h^L\_i的神经元节点数也是h\_size。Concatenating h^L\_0和h^L\_1得到长度为h\_size \* 2的neural vectors h^L。h^L依次经过一个全连接层和一个softmax得到output layer o^L。o^L是一个长度为|M0|\*|M1|的vector，其每个分量表示，给定输入symbol sequence s = (s0, s1)，的每个取值的概率，即P( |s0, s1)。

在实验中，h\_size取一组离散的取值，用于定量地表示agents模型的capacity。

The agents apply their own policy to play the referential game. Denote the policy of the speaker agent S and the listener L as $\pi\_S$ and $\pi\_L$. $\pi\_S$ indicates the conditional probability $P(s\_0|t)$ and $P(s\_1|t)$. $\pi\_L$ indicates the conditional probability $P(\hat{t}|s\_0,s\_1)$. The listener agent output predict result $\hat{t}$ through random sampling on the conditional probability $P(\hat{t}|s\_0,s\_1)$. The neural networks are used to simulate the agent policy. The agent architecture is shown in Figure 1.

For the speaker, the input object t is firstly passed to a MLP to get a hidden layer vector h^S. Then, the hidden layer vector is split into two feature vectors h\_0^S and h\_1^S with length h\_size. Through a MLP and a softmax layer, these feature vectors are transformed as the output o\_0 and o\_1 with the length |V| respectively. Lastly, the symbol sequences s\_0 and s\_1 are sampled from the output o\_0 and o\_1.

For the listener, the input symbol sequences s\_0 and s\_1 are passed into a MLP respectively to get the hidden layer vectors h\_0 and h\_1. The length of each vector is h\_size. Concatenating these vectors, and passing the conjunctive vector into a MLP and a softmax layer, the output o^L with length $|M\_0||M\_1|$ denotes P(\hat{t}|s\_0,s\_1). Lastly, the predict result is sampled from the output o^L.

In the experiments, the symbol h\_size is used to denote the model capacity of the agents.

*#subsection3: Training Algorithm*

在我们的实验中，我们使用Stochastic Policy Gradient methodology单独训练speaker agent S和listener agent L。我们用theta^S和theta^L分别表示speaker和listener的policy pi^S和pi^L的全部参数。训练speaker时，固定policy pi^L的参数theta^L，训练目标是调整参数theta^S，使其基于策略pi^S获得的期望奖励J(theta^S, theta^L) = E\_pi^S\_pi^L[R(t, t^)]最大。同理，训练listener时，固定policy pi^S的参数theta^S，最大化期望奖励J(theta^S, theta^L)。同时，为了排除其他因素，以及最小化人为诱导对emergent language的影响，我们仅使用listener预测结果是否正确作为奖励，分别对listener agent L和speaker agent S计算训练目标J(theta^S, theta^L)的gradients：

In this paper, the Stochastic Policy Gradient methodology is used to train the speaker and the listener respectively. The symbol $\theta\_S$ and $\theta\_L$ denote the neural network parameters of the policy $\pi\_S$ and $\pi\_L$ respectively. When training the speaker, the parameter $\theta\_L$ is fixed, and the training objective is to maximize the expected reward $ J(theta\_S, theta\_L) = E\_{\pi\_S,\pi\_L}[R(t, t^)]$ through adjusting the parameter $\theta\_S$. In a similar way, the listener is trained to maximize the expected reward$ J(theta\_S, theta\_L)$ by fixing the parameter $\theta\_S$ and adjusting the parameter $\theta\_L$. To minimize the influence of artificial induction on emergent language, we only use the predict result $\hat{t}$ of the listener agent as the evidence of whether giving the positive rewards. Then, the gradients of the expected reward $ J(theta\_S, theta\_L)$ can be calculated as follows:

\begin{align}

\nabla\_{\theta^S} J &= \mathbb{E}\_{\pi^S, \pi^L} \left[ R(\hat{t}, t) \cdot \nabla\_{\theta^S} \log{\pi^S(s\_0, s\_1 | t)} \right] \\

\nabla\_{\theta^L} J &= \mathbb{E}\_{\pi^S, \pi^L} \left[ R(\hat{t}, t) \cdot \nabla\_{\theta^L} \log{\pi^S(\hat{t} | s\_0, s\_1)} \right]

\end{align}

（这里的m换成s\_0, s\_1）

（这里的m,c换成s\_0, s\_1）

agents的模型相互独立，不共享任何模型参数也没有结构上的直接相连，模型之间的联系仅为相互传递symbol sequence s = (s\_0, s\_1)。训练过程如figure2所示。训练过程中，两个agents模型交替更新；并且使用一个平行的神经网络保存old parameters，该网络定期将参数与用于实际输出的网络的参数同步，从而限制policy的更新幅度，使训练过程更加稳定。

Unlike previous studies[][], the agents in this paper are totally independent. It means that all the neural networks parameters of each agent are not shared, and there are not any connection between the architecture of the neural networks. The training procedure is shown in Figure 2. The training process is the alternations of two procedure: the speaker training and the listener training. When one agent is training, the parameters of the other agent are fixed.

\begin{algorithm}[!h]

\caption{OurAlgorithm$(t,\hat{t})$}

\begin{algorithmic}[1]

\IF{Training the speaker agent S}

\FOR{Batch T randomly selected from $M\_0\times M\_1$}

\FOR{$t=(c\_0,c\_1)$ in T}

\STATE $P(s\_0|t),P(s\_1|t)=\pi\_{old}^S(s=(s\_0,s\_1)|t)$

\STATE Sample $s\_0$ with $P(s\_0|t)$, $s\_1$ with $P(s\_1|t)$

\STATE $P(\hat{t}|s) = \pi^L(\hat{t}|s)$

\STATE Sample $\hat{t}$ with $P(\hat{t}|s)$

\STATE Get reward $R(\hat{t},t)$

\STATE $J(\theta^S,\theta^L)=E\_{\pi\_{old}^S,\pi^L}[R(\hat{t},t)\cdot\frac{\pi^S(s|t)}{\pi^S\_{old}(s|t)}]$

\STATE Update $\theta^S$ by $\bigtriangledown\_{\theta^S}J$

\ENDFOR

\STATE $\pi\_{old}^S\leftarrow \pi^S$

\ENDFOR

\ENDIF

\IF{Training the listener agent L}

\FOR{Batch T randomly selected from $M\_0\times M\_1$}

\FOR{$t=(c\_0,c\_1)$ in T}

\STATE $P(s\_0|t),P(s\_1|t)=\pi^S(s=(s\_0,s\_1)|t)$

\STATE Sample $s\_0$ with $P(s\_0|t)$, $s\_1$ with $P(s\_1|t)$

\STATE $P(\hat{t}|s) = \pi^L\_{old}(\hat{t}|s)$

\STATE Sample $\hat{t}$ with $P(\hat{t}|s)$

\STATE Get reward $R(\hat{t},t)$

\STATE $J(\theta^S,\theta^L)=E\_{\pi\_{old}^S,\pi^L}[R(\hat{t},t)\cdot\frac{\pi^L(s|t)}{\pi^L\_{old}(s|t)}]$

\STATE Update $\theta^L$ by $\bigtriangledown\_{\theta^L}J$

\ENDFOR

\STATE $\pi\_{old}^L\leftarrow \pi^L$

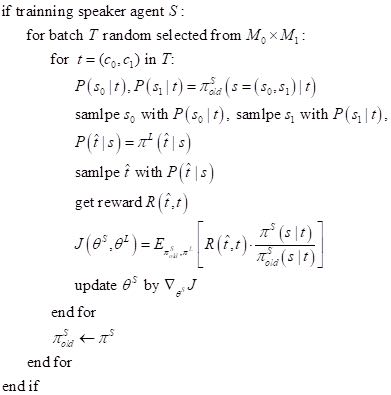
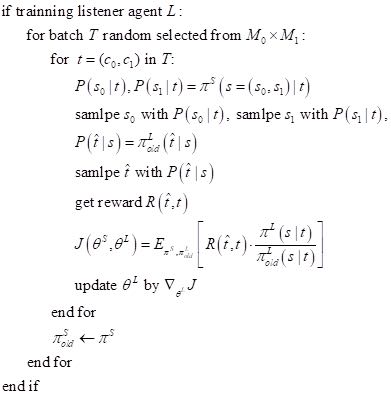
\ENDFOR

\ENDIF

\end{algorithmic}

\end{algorithm}

Figure2. Training Algorithm of agents

*#subsection4: Evaluation*

我们的目的是在保证模型收敛的前提下，研究模型的capacity和emergent language的compostionality的关系。当Listener agent L的正确率收敛到100%时，我们认为模型收敛，此时结束训练。所以，在完成一次训练后，我们从2个方面对模型进行评估：模型的capacity；emergent language的compostionality。

Our objective is to study the relationship between the agent model capacity and the compositionality of the emergent language, within the range afforded by the need for successful communication. When the accuracy of the listener converges to 100\%, it is believed that the training process is finished. With one training process, the agent model is evaluated through two aspects: the model capacity and the compositionality of the emergent language.

Agents的capacity可以由神经网络模型的隐层节点数(i.e. h\_size)量化衡量。扩写。

对于compostionality，据我们所知，目前并没有一个统一的度量标准。Topographic similarity (Brighton and Kirby, 2006)是一个广为接受的compostionality的度量(e.g., Lazaridou et al., 2018; Li and Bowling, 2019). Topographic similarity计算的是symbol sequence的minimum edit distance和object的差异度之间的Spearman correlation。In our case，symbol sequence s = (s\_0, s\_1)，object t = (c\_0, c\_1)，higher topographic similarity means similar objects have more similar symbol sequences in context. *Compositionality and Generalization in Emergent Languages*这篇文章指出topographic similarity is agnostic about the type of similarity as long as it is captured by minimum edit distance，并且提出了一个metric posdis。Posdis captures the intuition that each symbol should only be informative about a single concept.

**Theoretical Analysis**

In this section, we analyze the relationship between compositionality and agent capacity theoretically on the basis of mutual information theory. The process of theoretical analysis have three parts:

1. We use the Markov Series Channel (MSC) to model the language transmission process and use the probability distribution of symbols and concepts to model policies of agents.
2. We propose the metric \emph{MIS} to measure compositionality by calculating the similarity between columns of the mutual information matrix and the one-hot vector.
3. We explain why lower \emph{MIS} (i.e., compositionality) require higher agent capacity.

*subsection1: the Markov Series Channel (MSC)*

We use the MSC to model the language transmission process in a speaker-listener referential game. MSC is formed by a series of multiple sub-channels, and the information transmission among them has the Markov property, i.e., the value of next node depend only on the present one.

In our case, the speaker agent $S$ can be regard as one sub-channel in MSC, whose input is a concept sequence $c = ($c\_0, c\_1$) and output is a symbol sequence $s = ($s\_0, s\_1$); the listener agent $L$ can be regard as the other sub-channel, whose input is a symbol sequence $s = ($s\_0, s\_1$) and output is a predict result $\hat{t} = (\hat{c}\_0, \hat{c}\_1)$. The MSC structure in a listener-speaker referential game is shown in Figure5. We can model the policy of speaker agent by the probability distribution $P(s\_0 | t = (c\_0, c\_1))$ 和 $P(s\_1 | t = (c\_0, c\_1))$; The policy of listener can be modeled by the probability distribution $P(\hat{t} = (\hat{c}\_0, \hat{c}\_1) | s\_0, s\_1)$.

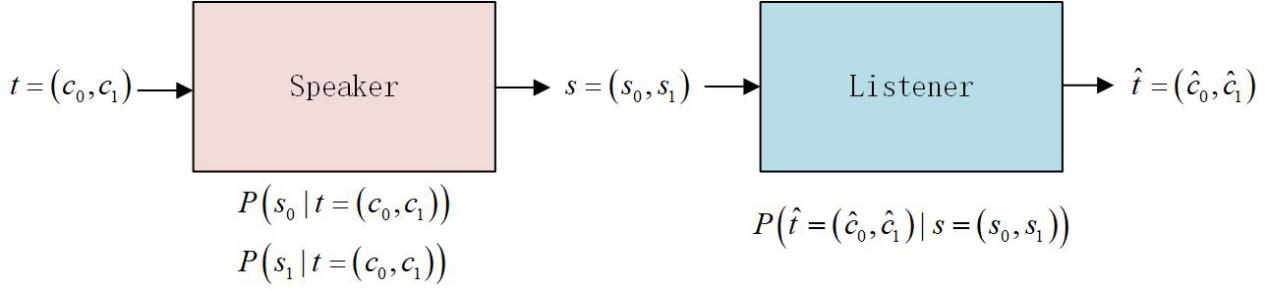


Figure5. the MSC model in a listener-speaker referential game

*subsection2: Mutual Information*

Mutual information $MI(X, Y)$ measures how much more is known about one random [value](https://simple.wikipedia.org/wiki/Value" \o "Value) when given another []. [Without](C:/Users/haoyi/AppData/Local/youdao/dict/Application/8.9.4.0/resultui/html/index.html" \l "/javascript:;) [loss](C:/Users/haoyi/AppData/Local/youdao/dict/Application/8.9.4.0/resultui/html/index.html" \l "/javascript:;) [of](C:/Users/haoyi/AppData/Local/youdao/dict/Application/8.9.4.0/resultui/html/index.html" \l "/javascript:;) [generality](C:/Users/haoyi/AppData/Local/youdao/dict/Application/8.9.4.0/resultui/html/index.html" \l "/javascript:;), if we regard $X$ as the information resource, $MI(X, Y)$ represents the amount of information from $X$ in $Y$.

Formula(1)

\newcommand\XX{\mathbb{X}}

\newcommand\YY{\mathbb{Y}}

\[

MI(X, Y) = \sum\_{Y \in \YY} \sum\_{X \in \XX} p(X, Y) \log{\left( \frac{p(X, Y)}{p(X) p(Y)} \right)}

\]

We obtain $MI(X, Y)$ by Formula (1), where $P(X, Y)$ is the joint probability distribution function of $X$ and $Y$; $P(X)$ and $P(Y)$ are the marginal probability distribution functions of $X$ and $Y$ respectively. The information entropy $H(X)$ tells how much [information](https://simple.wikipedia.org/wiki/Information" \o "Information) there is in the information resource $X$. We obtain $H(X)$ by Formula(2).

Formula(2)

\[

H(x) = - \sum\_{x \in X} P(X) \cdot \log{P(x)}

\]

*subsection3: the ‘Bilateral’ Metric MIS*

On the basis of the MSC model and mutual information theory, we analyze the information transmission process and propose a metric for compositonality. In our case, the transmission path of semantic information in the MSC is $t = (c\_0, c\_1)$ -> $s=(s\_0, s\_1)$ -> $\hat{t} = (\hat{c}\_0, \hat{c}\_1)$. When a stable language emerged, the speaker and listener should consistently use a specific symbol sequence s to refer a specific object t. Under such a constraint, the information from $t$ in $\hat{t}$ transmitted by $s$ can be obtained by Formula (3). The information in $t$ can be measured by the information entropy $H(t)$, and be obtained by the same way as Formula(2).

Formula (3)



We define the ratio $RI(t, s)$ of the information from t transmitted by s in the MSC, which can be obtained by Formula (4). $RI(t, s)$ also measures the degree of alignment between symbol sequences and objects.

Formula (4)



Following the Formula(4), we can calculate the ratio $RI(c\_i, s\_j)} (i = 0,1; j=0,1)$ of the semantic information from $c\_i$ transmitted by $s\_j$ respectively. We collect all $RI(c\_i, s\_j)} (i = 0,1; j=0,1)$ and obtain the mutual information matrix $MRI^B$ by Formula(5).

Formula (5)



$\MRI^B$ quantitatively represent the semantic information from $(c\_0, c\_1)$ transmitted by $(s\_0, s\_1)$ in the MSC, and each column of $MRI^B$ correspond to the semantic information carried by one symbol.

We find that each column of $\MRI^B$ should be an one-hot vector for a perfectly compositional language, cause a symbol only transmit information of a certain concept exclusively. Therefore, the similarity between the columns of $MRI^B$ and a one-hot vector is higher, indicating the higher compostionality. We propose the metric \emph{MIS} to measure compositionality by calculating such similarity. Specifically, \emph{MIS} is the average cosine similarity between each column of $MRI^B$ and a one-hot vector. After normalization, \emph{MIS} is obtained by Formula(6).

Formula (6)

 (减号两端写反了)

（归一化有问题）



*subsection4: ‘Bilateral’ and ‘Unilateral’ Metrics*

We compare the ‘bilateral’ metric \emph{MIS} and other metrics for measuring compositionality. ‘Unilateral’ metrics, such as \emph{topo} (topographic similarity)[] and \emph{posdis}[], only calculates compotionality based on the policy of the speaker. We take an example, as shown in Figure2.5, to illustrate the inadequacy of ‘unilateral’ metric.

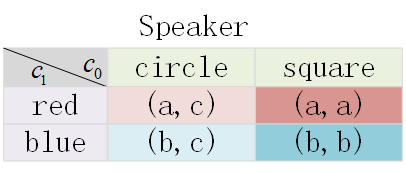
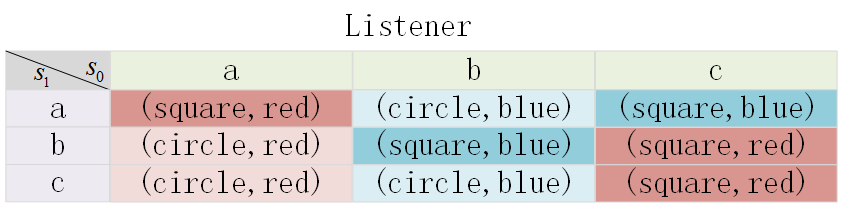
 

Figure 2.5: an emergent language case where the correspondences of speaker and listener to symbols and concepts are inconsistent

Figure2.5 shows an emergent language case where the correspondences of speaker and listener to symbols and concepts are inconsistent. In this case, the speaker uses $s\_0$ to represent color $c\_1$ and uses $s\_1$ to represent shape $c\_0$; but for the listener, $s\_0$ and $s\_1$ do not have any separate concepts corresponding to them. More specifically, when the speaker gives ‘$s\_1 = a$’, the message passed by the speaker is 'the shape is blue'; but the listener cannot distinguish the shape depend only on ‘$s\_1 = a$’. In other words, when we evaluate the language in this case from the perspective of speaker, it is a perfect compositonal language (i.e. topo = posdis = 1); but when from the perspective of listener, the compostionality would be different (i.e. topo < 1 and posdis < 1). Therefore, a ‘bilateral’ metric is needed to address this problem by taking the inconsistencies as described above into account. \emph{MIS} is a ‘bilateral’ metric and captures the view that a single symbol of emergent language with higher composionality should be used to ground or transmit a certain concept ‘bilaterally’ and more exclusively between listener and speaker.

*subsection5: MIS and Agent Capacity*

We fill the gap between \emph{MIS} and agent capacity with the complexity of semantic information, and analyze the correlation between them. We generalize the metric \emph{MIS} to the general case where multiple symbols $s\_j (j = 0,1...M-1)$ corresponds to several concepts $c\_i (I = 0,1..., N-1)$. The general \emph{MIS} and $MRI^B$ can be obtained by Formula(7).

Formula (7)



The $j-th (j = 0,1...M-1)$ column vector of $MRI^B$ represents the ratio of information transmitted by symbol $s\_j$ to all $N$ concepts. \emph{MIS} comes lower indicates that the emergent language tends to delivery semantic information about more concepts in each symbol, so that the complexity of semantic information carried by one symbol tend to be higher. For example, Figure6 shows the $MRI^B$ of the language with low \emph{MIS} $L\_low$ and high \emph{MIS} $L\_high$ respectively. In this example, though observing the column vectors in each $MRI^B$, we can clearly find that each symbol in $L\_low$ carry more concepts’ semantic information. As a result, higher agent capacity is required to characterize the more complex semantic information when \emph{MIS} (i.e., compositionality) is lower.

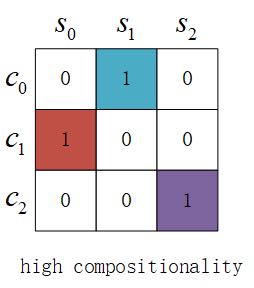
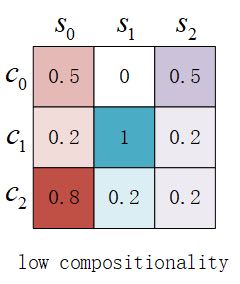
 

Figure6: $MRI^B$ of the language with low \emph{MIS} $L\_low$ and high \emph{MIS} $L\_high$

**Experiments in Teaching Artificial Language**

In this section, we verify that agent need higher capacity to master an artificial language with lower compositionality under the scenario of language teaching. Specifically, we arrange a preassigned alignment between symbol sequence $s = (s\_0, s\_1)$ and object $t=(c\_0, c\_1)$ as an artificial language. After that, we fabricate the speaker to output artificial languages with different compostionality respectively, and train the listener to learn the artificial language.

Our settings in the experimental framework are as follows：

a). object $t = (c\_0, c\_1)$, concepts size $|M\_0| = |M\_1| = 3$, $M0 = {circle, square, triangle}$, $M1 = {red, blue, green}$;

b). symbol sequence $s = (s\_0, s\_1)$，vocabulary size $|V|=9$, $s\_i (i=0,1) = {a, b, c, d, e, f, g, h, i}$;

c). Count of neural nodes in the hidden layer $h\_size = {1,2,3,4,5,6,7,8}$.

We arrange 3 artificial languages with different compositionality, as shown in Figure3 respectively. Figure3(a) shows a perfect compositional language $LA$ with maximum compostionality (i.e., \emph{MIS = 1} after training). For the symbol sequence $s = (s\_0, s\_1)$ in $LA$, $s\_0$ represent shape and $s\_1$ represent color. Figure3(b) $LB$ shows an artificial language with a certain compositionality (i.e., \emph{MIS} = XX after training). In $LB$, $s\_0$ and $s\_1$ can’t be used separately to distinguish shape or color. Figure3(c) represents a non-compositional language $LC$ with minimum compostionality (i.e., \emph{MIS} = XX after training). In $LC$, $s\_0$ represent a shape-color pair but $s\_1$ is meaningless.

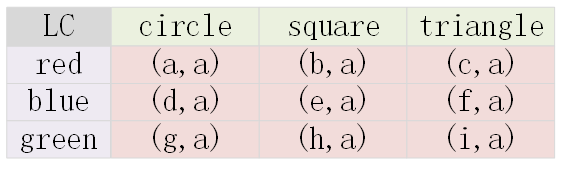
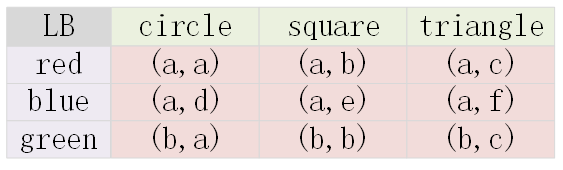
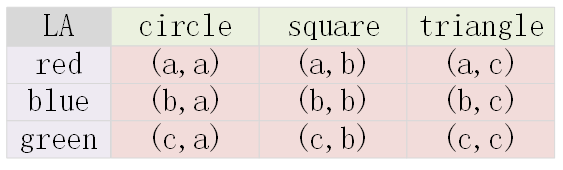


Figure3. (a): a perfect compositional language $LA$ with \emph{MIS = 1}; (b): an artificial language $LB$ with \emph{MIS} = XX; (c): a non-compositional language $LC$ with \emph{MIS} = XX.

Teaching $LA$, $LB$ and $LC$ respectively to a listener agent and change its capacity by adjusting h\_size, we obtain the accuracy-batch curve as shown in Figure4. Figure4(a) shows that when $h\_size$ equals to 1, the agent capacity is too low to handle languages. Figure4(b) shows that when $h\_size$ equals to 2, agent can only learn $LA$ whose compositionality (i.e. \emph{MIS}) is highest in all 3 languages. Combing these two observations, we can infer that language with lower compostionality need higher agent capacity to ensure communicating successfully (i.e., $h\_size$). Figure4(c) to (h) show that the higher agent capacity cause a faster training process for all three languages, but the improvement for different languages is quite different. Figure5 shows such difference more clearly and we find that $LC$ whose compositionality is lowest get the largest improvement. So it is obvious that language with lower compostionality also need higher agent capacity to training faster. In conclude, teaching an artificial language with lower compositionality to agent require higher agent capacity both for learning successfully and training faster.

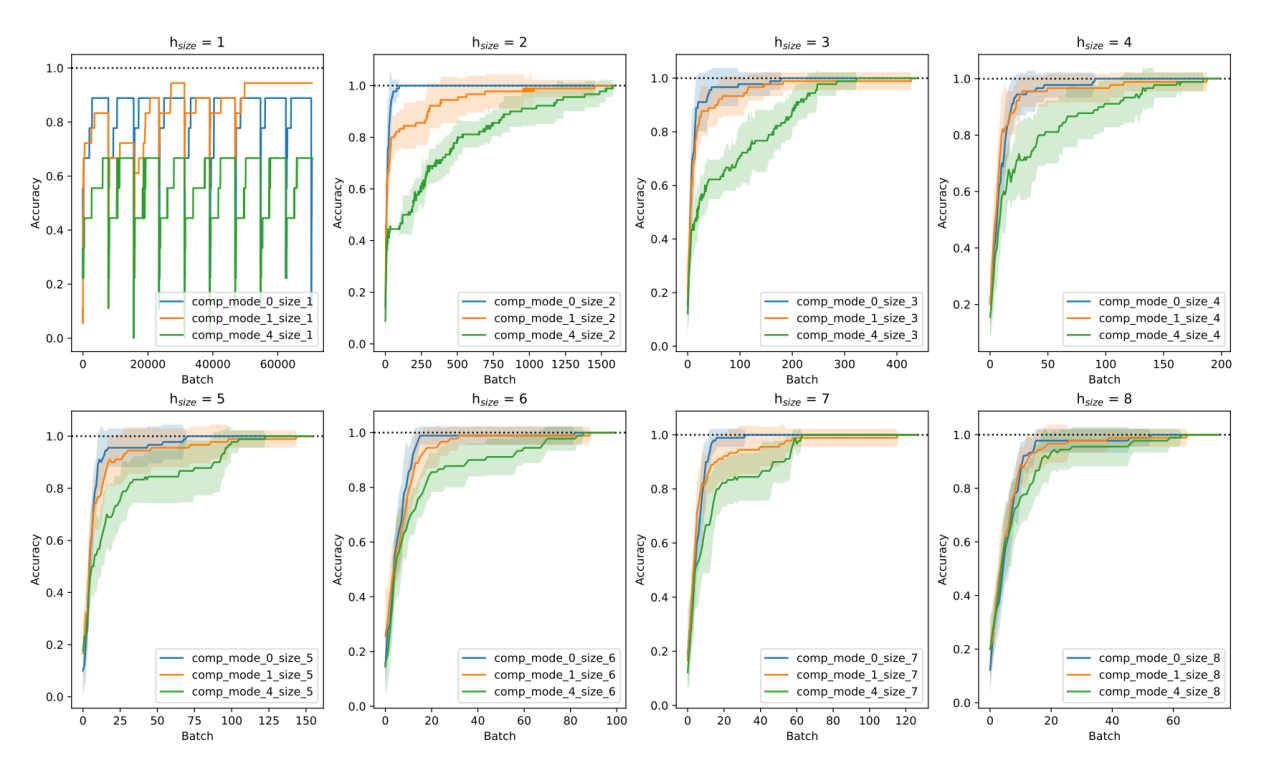


Figure4. (a) to (h) respectively shows the accuracy-batch curve during the training process of the listener with different capacity (i.e., $h\_size$ = 1,2,...,8). Each curve represents an average accuracy trend from 50 repeated training, and the shadow alongside each curve represents the range from $\mu - \sigma$ to $\mu + \sigma$. Given $\mu$ is the average accuracy and $\sigma$ is the standard deviation.

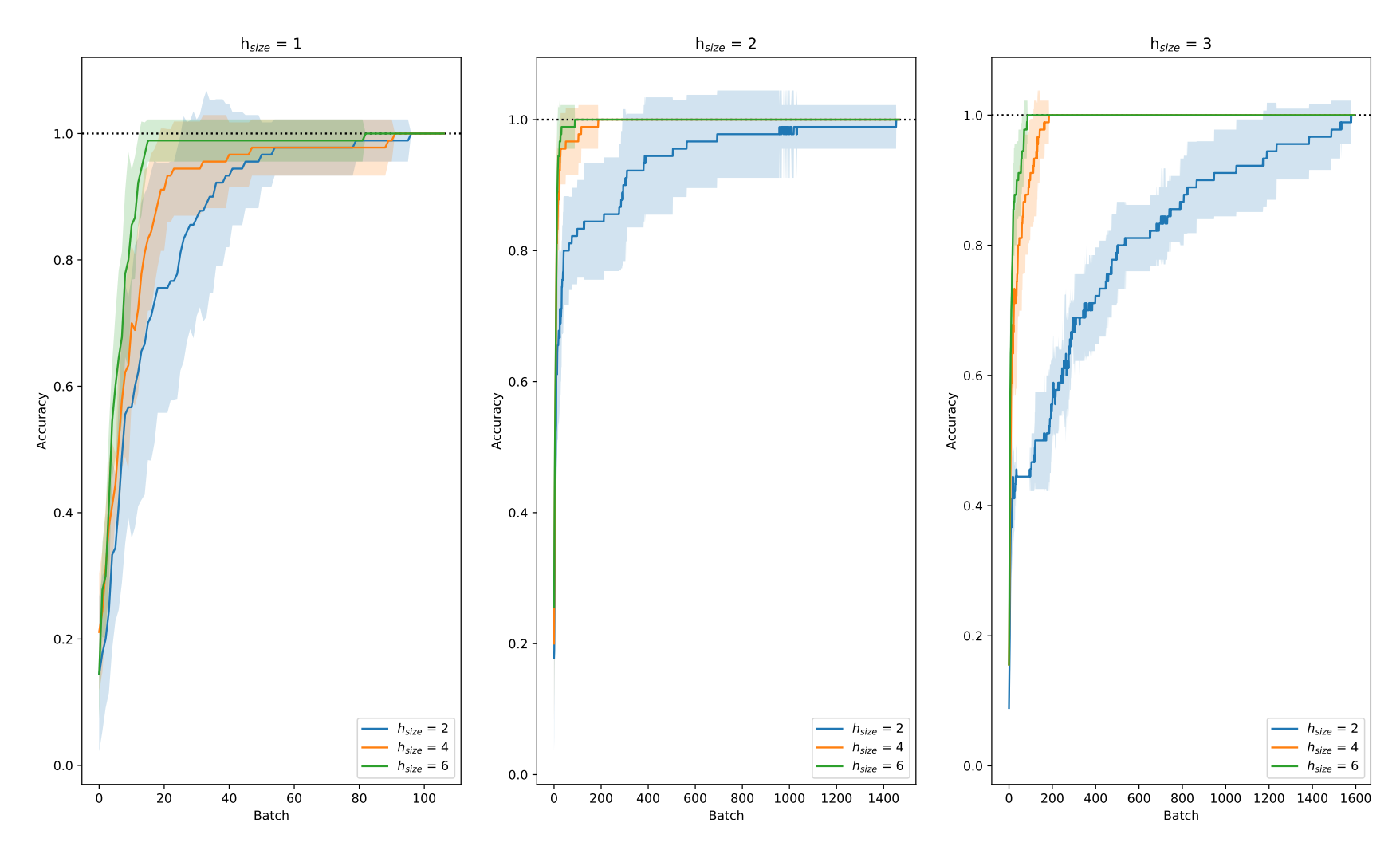


Figure5. (a), (b) and (c) respectively shows the accuracy-batch curve during teaching the artificial language $LA$, $LB$ and $LC$ to the listener. Each curve also has the average and the standard deviation.

**Experiments in Emergent Language**

*#In this section, we verify the hypothesis above mentioned by experimental results*

Our second experiment is to verify that lower agent capacity would facilitate higher compostionality under a scenario of language emergence. Specifically, we training a speaker and a listener to create a communication protocol (i.e., emergent language), so that the listener can select the same object which is received by the speaker.

实验选取3组concept size和vocabulary size的配置如下：

1. Concept size |M0| = 3, |M1| = 3，vocabulary size |V| = 4；
2. Concept size |M0| = 3, |M1| = 3，vocabulary size |V| = 6；
3. Concept size |M0| = 3, |M1| = 3，vocabulary size |V| = 10；

在每组配置中，改变模型的capacity (i.e. h\_size)，并对每个h\_size的agents训练多次至收敛，即分别产生多个语言。h\_size的取值如下：

h\_size = {6,8,10,15,20,30,40,...,100}

分别统计产生语言的compostionality (measured by MIS)的平均值和标准差。

得到3种配置下的MIS-h\_size曲线如Figure7所示。

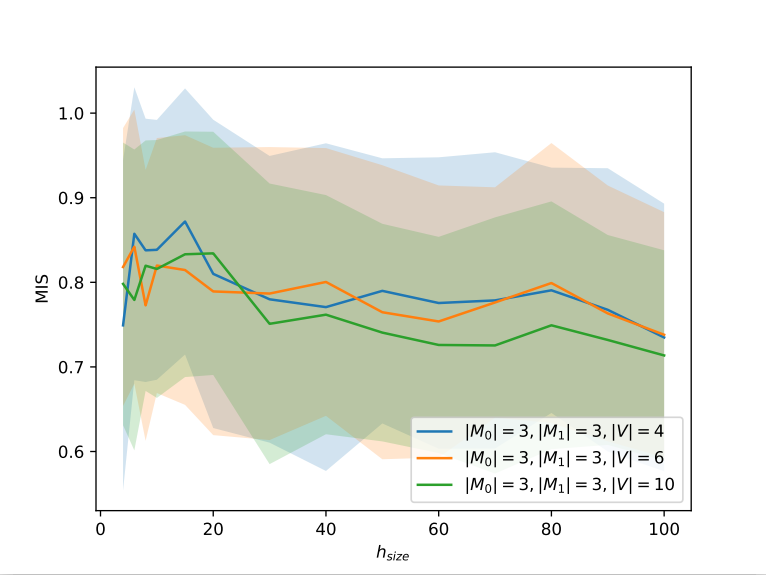


Figure7. 不同concept size和vocabulary size配置下，MIS-h\_size曲线图。其中实线上的点代表均值mu，实线周围的阴影代表取值范围[mu - sigma, mu + sigma]，sigma为标准差。

从Figure7中可以看出，随着h\_size升高，MIS的均值呈明显的下降趋势。以Concept size |M0| = 3, |M1| = 3, vocabulary size |V| = 10的配置为例：当h\_size <= 20时，MIS的均值在0.8附近；当20 < h\_size <= 40时，MIS的均值有明显的下降趋势，并且在0.75到0.8之间浮动；当h\_size > 40时，MIS的均值基本在0.7到0.75之间浮动。对于不同的h\_size，标准差的区别不大，MIS都有较大的随机性波动，与introduction中介绍的motivation相符（在缺少诱导的环境中，产生的语言的组合性波动较大）。由此可得，更低的capacity有利于提升产生语言的组合性。

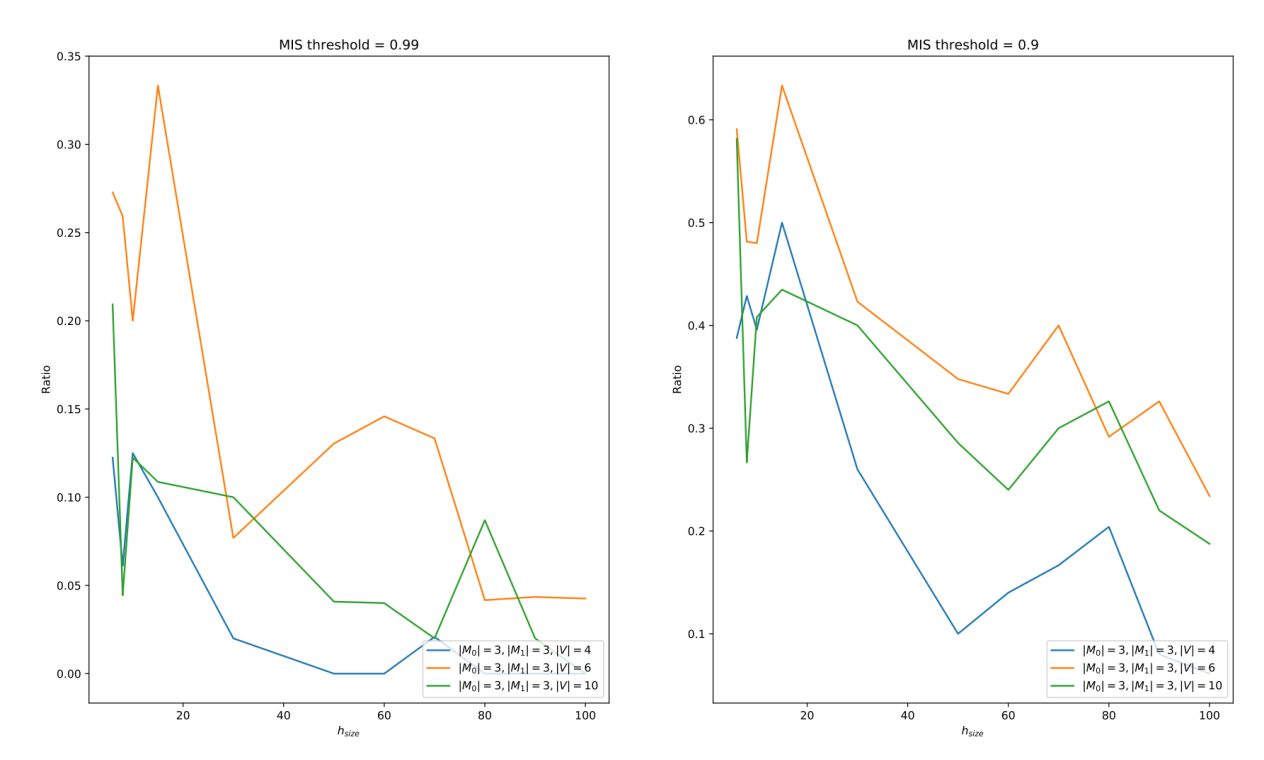


Figure8. (a). 不同concept size和vocabulary size配置下，agent产生语言的MIS >0.99（近乎完美组合的语言）的比例随h\_size的变化曲线；(b). 不同concept size和vocabulary size配置下，agent产生语言的MIS >0.90的比例随h\_size的变化曲线。

我们从所有生成的语言中筛选出较高组合性的语言，观察产生高组合性语言的比例ratio与h\_size的关系。上述高组合性的判定标准选取两种：(a). MIS>0.99; (b). MIS > 0.9。分别得到ratio和h\_size的曲线如Figure8(a) (b)所示。以Concept size |M0| = 3, |M1| = 3, vocabulary size |V| = 4的配置为例：h\_size < 20时，MIS > 0.99的比例在10%附近，MIS > 0.9的比例在40%附近；当20 < h\_size <= 40时，MIS > 0.99的比例随h\_size的增大急速下降，且在0到5%之间浮动，MIS > 0.9的比例在15%到50%之间浮动；当h\_size > 40时，MIS > 0.99的比例在3%以内浮动，MIS > 0.9的比例降至20%以内。由此，我们发现当h\_size的取值较大时，无论h\_size如何选取，agent capacity足够掌握任何组合性的语言，此时h\_size对语言组合性的影响不明显；当h\_size的取值较小时，进一步降低h\_size将使得agent很难掌握低组合性的语言，从而逼迫agent使用高组合性的语言完成referential game，此时h\_size对语言组合性的影响显著，且对于掌握高组合性语言十分有利。

**Conclusion**

**Reference**