Conceptual structure is shaped by competing pressures for simplicity and informativeness

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Pressures shaping language
Pressures shaping language
Pressures shaping language

Language

Simplicity
Informativeness

Learning
Communication
Pressures shaping language

Language

Simplicity
Informativeness

Induction
Interaction
Kinship terms are simple and informative

Kinship Categories Across Languages Reflect General Communicative Principles
Charles Kemp and Terry Regier

Languages vary in their systems of kinship categories, but the scope of possible variation appears to be constrained. Previous accounts of kin classification have often emphasized constraints that are specific to the domain of kinship and are not derived from general principles. Here, we propose an account that is founded on two domain-general principles: Good systems, kin classification systems in the world’s languages, achieve a near-optimal trade-off between these two competing principles. We also show that our account explains specific patterns of variation in kinship terms.

Concepts and categories vary across cultures but may nevertheless be shaped by universal constraints (1–4). Cross-cultural studies have proposed universal constraints that help to explain how colors (5, 6), plants, animals (7–9), and spatial relations (10–12) are organized into categories. Kinship has traditionally been a prominent domain for studies of this kind, and researchers have described many constraints that help to predict which of the many logically possible kin classification systems are encountered in practice (13–15). Typically, these constraints are not derived from general principles, although it is often suggested that they are consistent with cognitive and functional considerations (2, 11–13, 15).

Here, we show that major aspects of kin classification follow directly from two general principles: Categories tend to be simple, which minimizes cognitive load, and to be informative, which maximizes communicative efficiency. Principles like these have been discussed in other contexts by previous researchers (16–19). For example, Zipf suggested that word-frequency distributions achieve a trade-off between simplicity and communicative precision (20, 21). Hawkins (22) has suggested that grammars are shaped by a trade-off between simplicity and communicative efficiency, and Rosch has suggested that category systems “provide maximum information with the least cognitive effort” (p. 190 of 23).
Kinship terms are simple and informative
Kinship terms are simple and informative.
Induction & interaction: Pressures for simplicity and informativeness
Induction & interaction: Pressures for simplicity and informativeness
Induction & interaction: Pressures for simplicity and informativeness

induction

Informative

Simple
Induction & interaction: Pressures for simplicity and informativeness
Induction & interaction: Pressures for simplicity and informativeness
Induction & interaction: Pressures for simplicity and informativeness
Induction & interaction: Pressures for simplicity and informativeness
Induction

as the pressure for simplicity
Induction and the simplicity prior
Induction and the simplicity prior
Induction and the simplicity prior
Induction and the simplicity prior

Principle of multiple explanations
Induction and the simplicity prior

Occam’s razor

Principle of multiple explanations
Induction and the simplicity prior

Occam’s razor

Principle of multiple explanations
Induction and the simplicity prior

\[ P(H|D) \propto P(H)P(D|H) \]
Interaction
as the pressure for informativeness
Regier et al.'s informativeness model

Speaker

Listener
Regier et al.’s informativeness model

Speaker

Listener

pov  zix  reb  wud
Regier et al.’s informativeness model
Regier et al.‘s informativeness model

Speaker

 Listener

zix

pov  zix  reb  wud
Regier et al.’s informativeness model
Regier et al.’s informativeness model

Speaker

Listener

pov zix reb wud
Can iterated learning give rise to informative categories?

Language evolution in the lab tends toward informative communication

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Abstract

Why do human languages tend to evolve into informative systems? One explanation is that, in the absence of pre-existing constraints on the evolution of language, the best way to evolve an informative system is to start with an uninformative system and then iteratively learn from more informative systems. This idea, known as iterated learning, has been shown to give rise to informative systems in laboratory settings, but it is not clear whether this process can be generalized to human language evolution. We address this question by investigating whether iterated learning can give rise to informative systems in the lab.

Keywords: Iterated learning, language evolution, natural language, cultural transmission, adaptation, categorization, semantic information.

The origins of semantic diversity

Languages vary widely in their fundamental units of meaning—the concepts and categories they encode. In simple words, there are two main types: concepts that capture the essence of an event or state of affairs, and categories that group together similar events or states of affairs. These categories are often organized in a hierarchical manner, with more general categories at the top and more specific categories at the bottom. This hierarchical structure is thought to reflect the way in which people perceive and organize the world around them.

Iterated learning and category systems

The general idea behind iterated learning studies is that of a chain or sequence of learners. The first person in the chain produces some behavior; the next person in the chain observes that behavior, learns from it, and then produces behavior of her own; that trained behavior is then observed by the next person in the chain, who learns from it, and so on. This experimental paradigm is meant to capture in miniature the acquisition and propagation of cultural information across generations; the learned behavior information is passed down through the chain of learners.
Can iterated learning give rise to informative categories?
Can iterated learning give rise to informative categories?

Carstensen, Xu, Smith, Regier (2015)
Can iterated learning give rise to informative categories?

Carstensen, Xu, Smith, Regier (2015)
Informativeness from learning biases

- Induction
- Induction & Interaction
- Interaction

Informative

Simple
Informativeness from learning biases

- Informative
- Simple

Cognitive biases
Bayesian model
Bayesian inference

\( \mathcal{L} = \{ \ldots \} \)
Bayesian inference

\[ \mathcal{L} = \{ \langle \cdot, \cdot \rangle, \langle \cdot, \cdot \rangle, \langle \cdot, \cdot \rangle, \ldots \} \]

\[ D = [\langle m_1, s_1 \rangle, \langle m_2, s_2 \rangle, \langle m_3, s_3 \rangle, \ldots, \langle m_n, s_n \rangle] \]
Bayesian inference

\[ \mathcal{L} = \{ \ldots \} \]

\[ D = [\langle m_1, s_1 \rangle, \langle m_2, s_2 \rangle, \langle m_3, s_3 \rangle, \ldots, \langle m_n, s_n \rangle] \]

\[
\text{likelihood}(D|L) = \prod_{\langle m, s \rangle} P(s|L, m)
\]

\[ = \]

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Bayesian inference

\[ \mathcal{L} = \{ \ldots \} \]

\[ D = [\langle m_1, s_1 \rangle, \langle m_2, s_2 \rangle, \langle m_3, s_3 \rangle, \ldots, \langle m_n, s_n \rangle] \]

\[
\text{likelihood}(D|L) = \prod_{\langle m, s \rangle} P(s|L, m)
\]

\[
\text{prior}(L) \propto 2^{-\text{complexity}(L)}
\]
Bayesian inference

\[ \mathcal{L} = \{ \quad \ldots \} \]

\[ D = [\langle m_1, s_1 \rangle, \langle m_2, s_2 \rangle, \langle m_3, s_3 \rangle, \ldots, \langle m_n, s_n \rangle] \]

\[
\text{likelihood}(D|L) = \prod_{\langle m, s \rangle} P(s|L, m)
\]

\[
\text{prior}(L) \propto 2^{-\text{complexity}(L)}
\]

\[
\text{prior}(L) \propto 2^{-\text{cost}(L)}
\]
Bayesian iterated learning under a simplicity prior
Bayesian iterated learning under a simplicity prior
Bayesian iterated learning under a simplicity prior
Bayesian iterated learning under a simplicity prior
Bayesian iterated learning under a simplicity prior
Bayesian iterated learning under a simplicity prior
Bayesian iterated learning under an informativeness prior
Bayesian iterated learning under an informativeness prior
Model results

- **Expressivity**
- **Transmission error**
- **Complexity**
- **Communicative cost**

*Graphs show the progression over generations with two priors: Simplicity prior (blue) and Informativeness prior (red).*
Experiment
Stage 1: Training

15 minutes

You are going to learn a simple language. We will train you on 4 words in the language and we will test how well you are learning the words. Try to learn the language as well as you can and aim to be accurate in your answers. You will receive a 2¢ bonus payment for every correct test answer. If you decide to stop the task, please click the EXIT button so that someone else can take part.

1. Look at the picture
   - This is a triangle

2. Learn the word
   - "This is a\textcolor{red}{t}ri\textcolor{red}{a}\textcolor{red}{g}\textcolor{red}{e}\textcolor{red}{l}"

3. Click on the word to confirm you learned it
   - What is it called?
   - \textcolor{red}{t}ri\textcolor{red}{a}\textcolor{red}{g}\textcolor{red}{e}\textcolor{red}{l}

4. Try to recall the correct word
   - What is this\textcolor{red}{t}ri\textcolor{red}{a}\textcolor{red}{g}\textcolor{red}{e}\textcolor{red}{l}?

5. If correct, you get a 2¢ bonus
   - \textcolor{red}{t}ri\textcolor{red}{a}\textcolor{red}{g}\textcolor{red}{e}\textcolor{red}{l}
This is a zix
What is it called?

reb  pov  wud  zix
Stage 2: Test

5 minutes

You have now completed the training stage! Next we will test you on the language that you just learned. For each picture, try to click on the correct word. You will get a $0.02 bonus payment for every correct answer. It is therefore possible to earn up to $1.28 in this stage of the task. However, this time we will not tell you if you are correct or incorrect. You will find out at the end how many you got correct.

START
What is this called? +2¢ if correct

pov  wud  reb  zix
Experimental stimuli

- Angle
- Size
Experimental stimuli

Canini et al. (2014)
Iterated learning with humans
Iterated learning with humans
Iterated learning with humans
Iterated learning with humans
Iterated learning with humans
Iterated learning with humans
Category systems that were converged on

1 category (2/12)

2 categories (1/12)

3 categories (8/12)

4 categories (1/12)
Experimental results
Experimental results

Expressivity decreases
Experimental results

Expressivity decreases
Compactness increases
Model fit
Estimating unknown parameters of the model
Estimating unknown parameters of the model
Estimating unknown parameters of the model

-input

-output

fit parameter values to maximize likelihood of participant output

$\pi_{\text{sim}}, \pi_{\text{inf}}$

$w \geq 0$

$\varepsilon \in (0,1)$
Model results with best-fit parameters
Simplicity prior

Informativeness prior
Conclusions
Languages are shaped under the simplicity–informativeness tradeoff by pressures from induction and interaction.

A rational learner with no prior expectations ought to apply Occam’s razor to domain-general problems of induction.
Iterated learning results in simple categorization systems through two mechanisms:

- **Restructuring**
- **Loss of expressivity**
Iterated learning results in simple categorization systems through two mechanisms:

1. Restructuring
2. Loss of expressivity

Iterated learning can give rise to informative languages without positing a bias for informativeness.
Iterated learning results in simple categorization systems through two mechanisms.

Iterated learning can give rise to informative languages without positing a bias for informativeness.

But! Unconstrained, iterated learning results in degenerate languages, so there’s still a role for interaction.
Thank you!
Take-home messages

Languages are shaped under the simplicity–informativeness tradeoff by pressures from induction and interaction.

A rational learner with no prior expectations ought to apply a simplicity principle to domain-general problems of induction.

Iterated learning (repeated induction) results in simple categorization systems through two mechanisms:

- **Compact categories**: Restructuring of the space ⇒ more informative
- **Loss of expressivity**: Loss of words/concepts ⇒ less informative

Iterated learning can give rise to informative(-ish) categories without actually positing a bias for informativeness; the languages are actually evolving to become simpler.

Nevertheless, interactional dynamics restrain languages from total degeneration.