Induction and interaction in the evolution of language and conceptual structure

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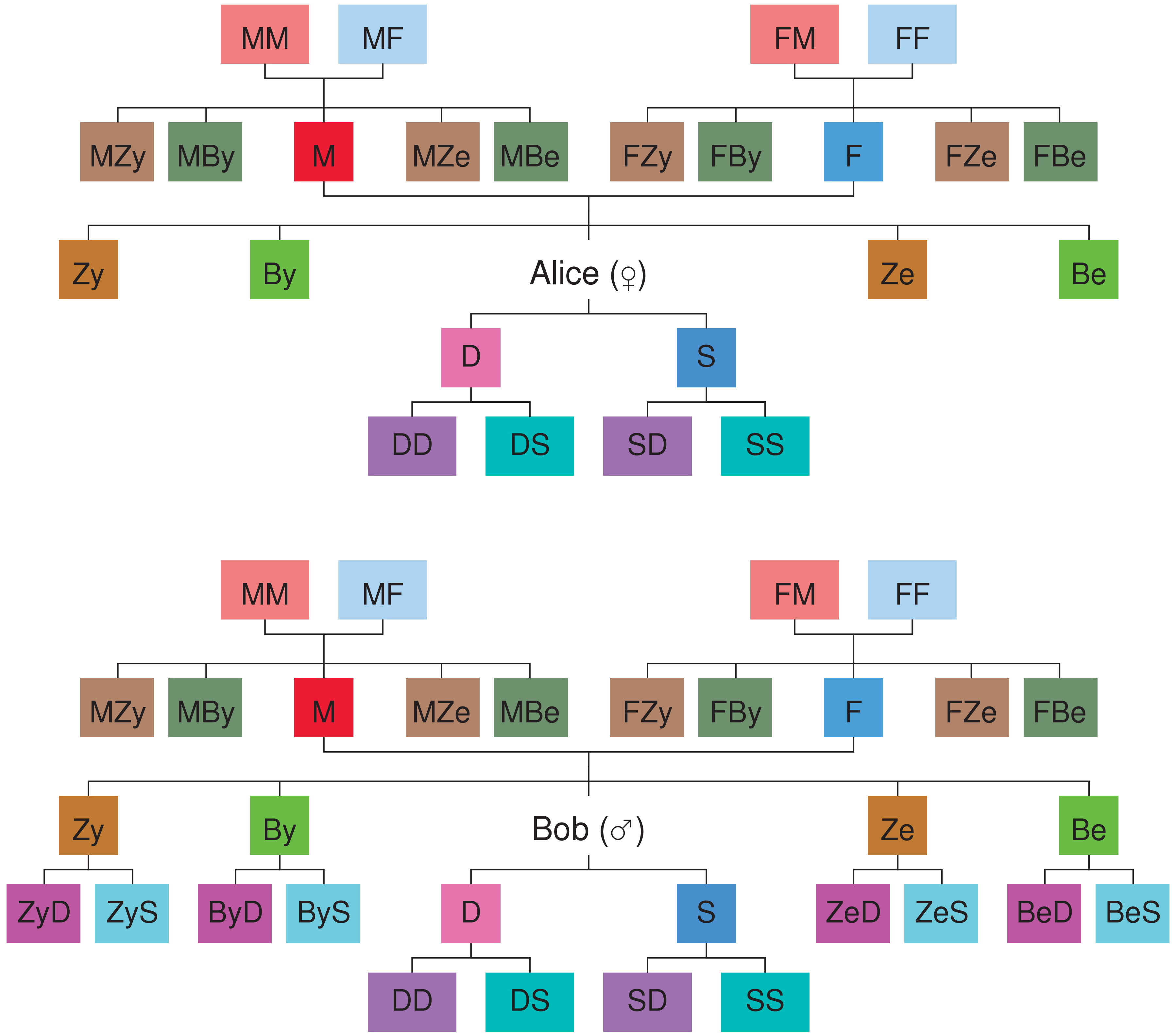
CENTRE for LANGUAGE EVOLUTION
E·S·R·C ECONOMIC & SOCIAL RESEARCH COUNCIL

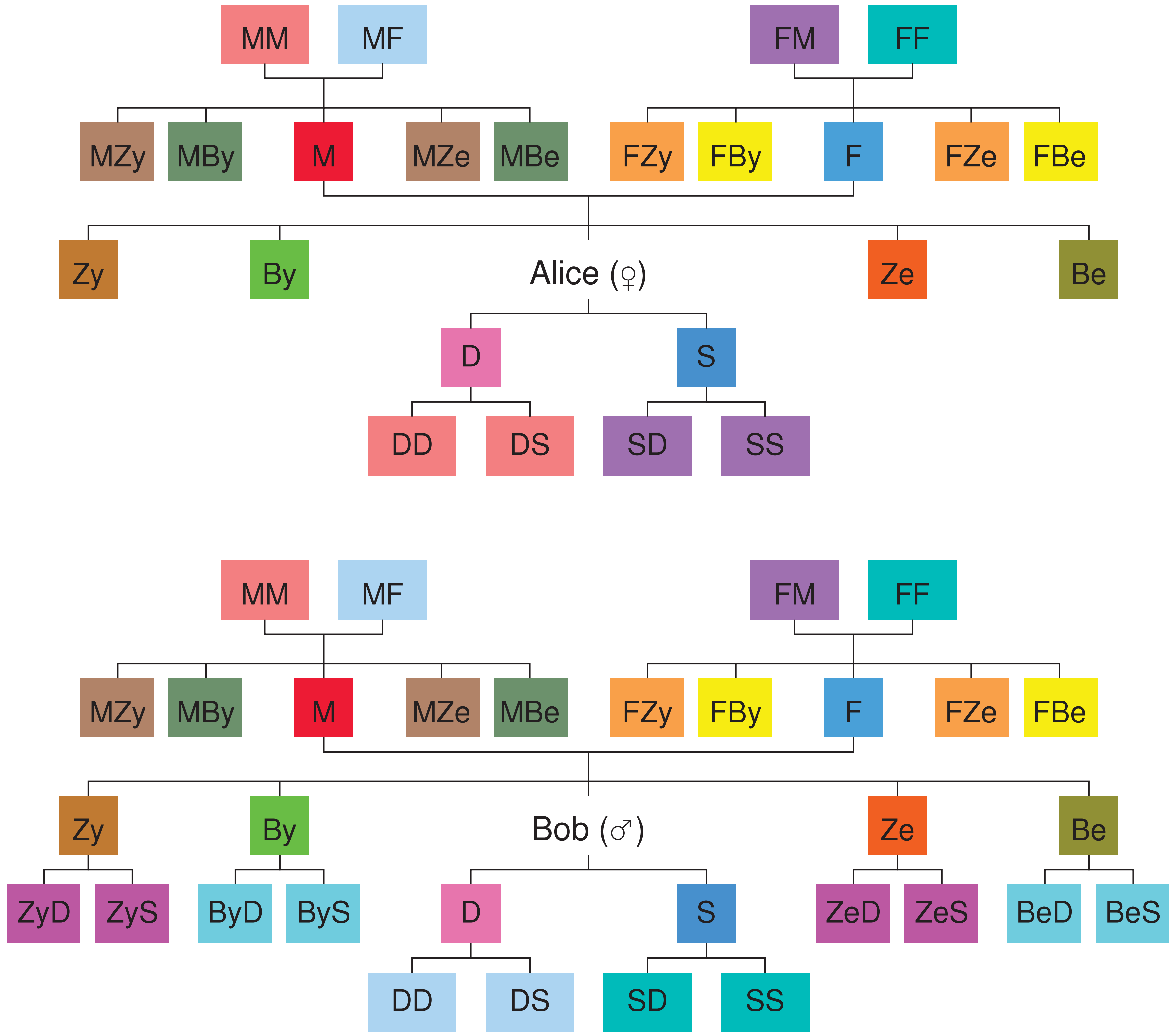
Kinship terms are simple and informative

Kemp & Regier (2012)

English



Northern Paiute



mother(x, y)	↔ PARENT(x, y) ∧ FEMALE(x)
father(x, y)	↔ PARENT(x, y) ∧ MALE(x)
daughter(x, y)	↔ CHILD(x, y) ∧ FEMALE(x)
son(x, y)	↔ CHILD(x, y) ∧ MALE(x)
sister(x, y)	↔ ∃z daughter(x, z) ∧ PARENT(z, y)

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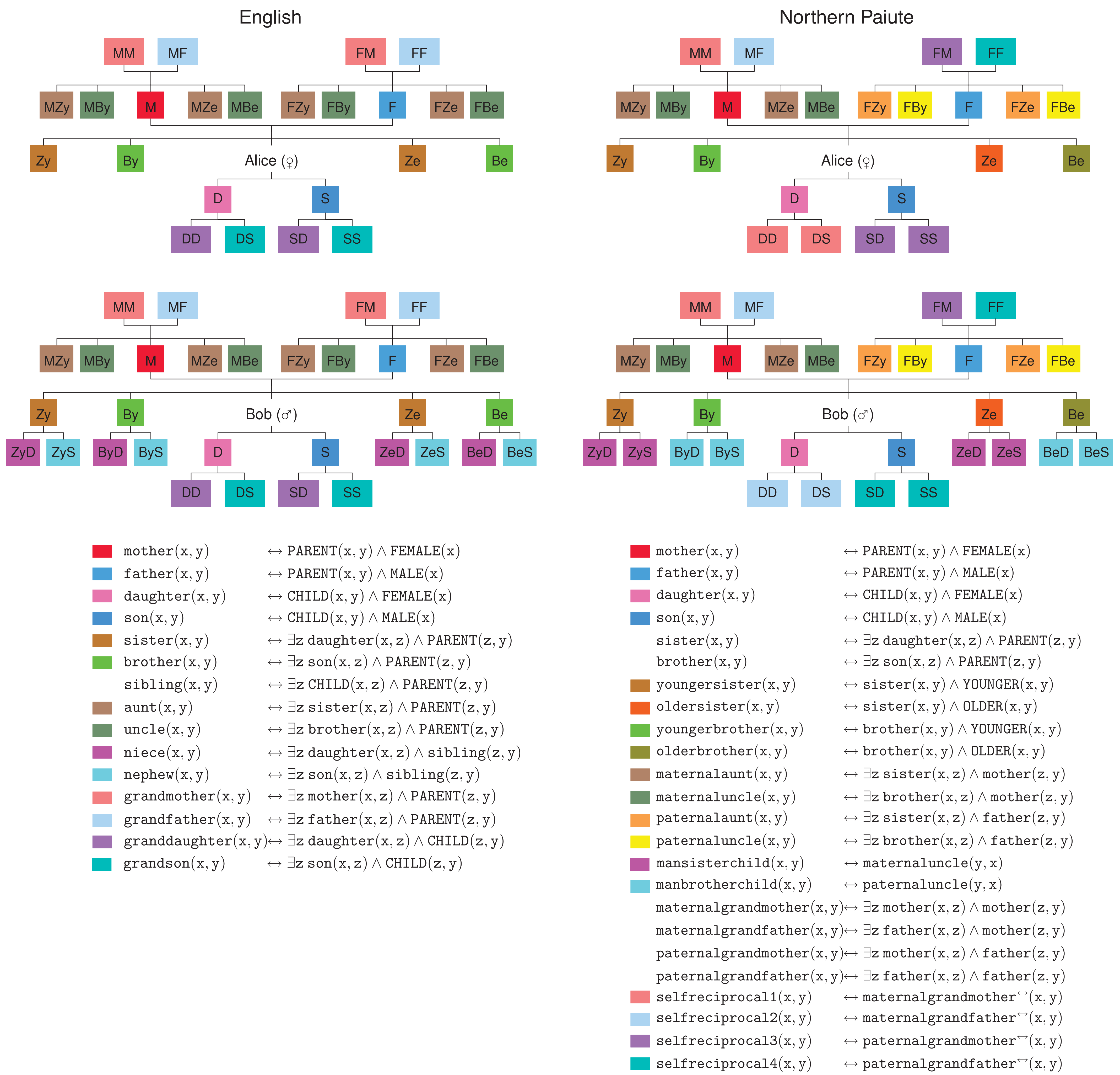
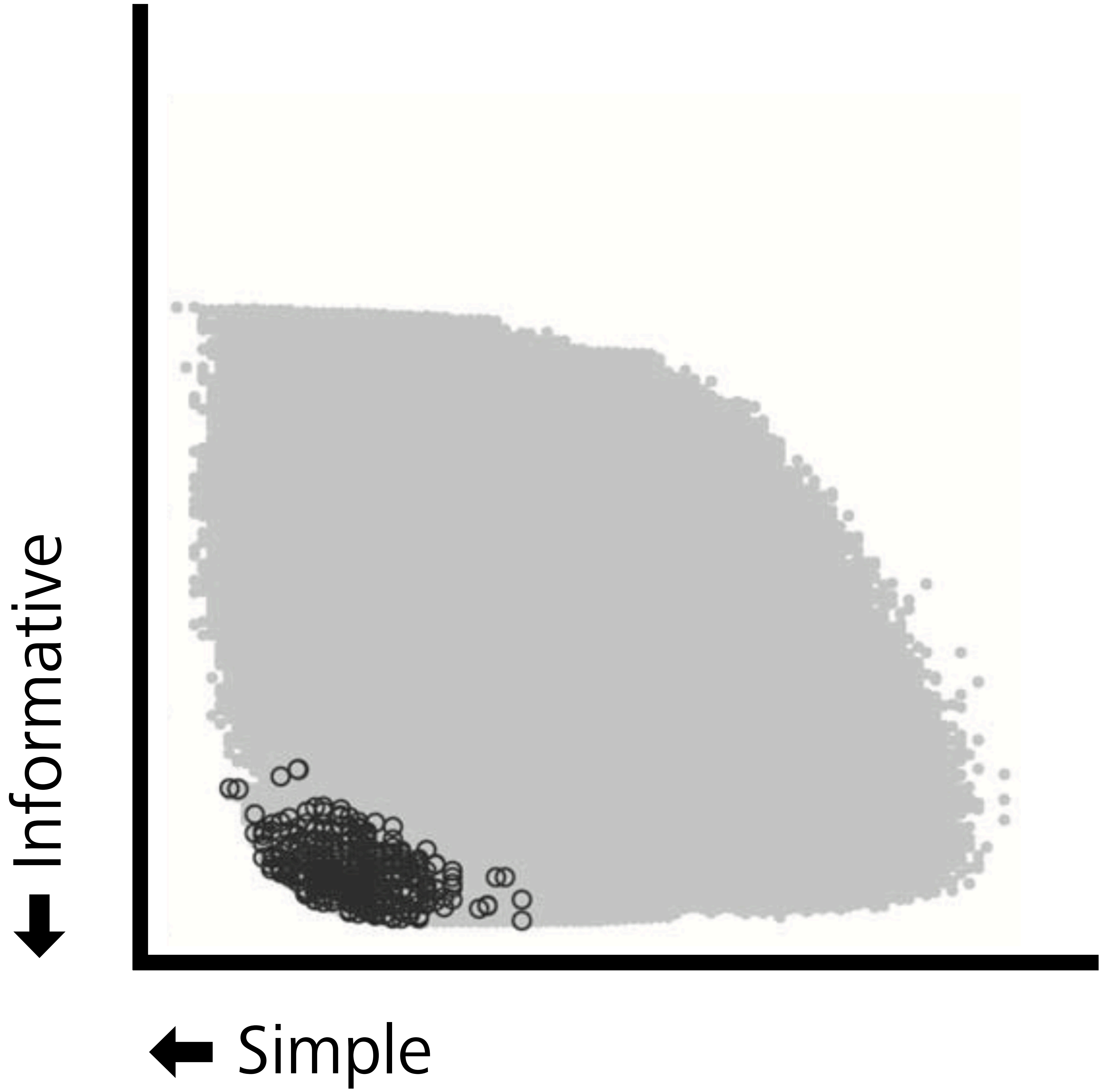
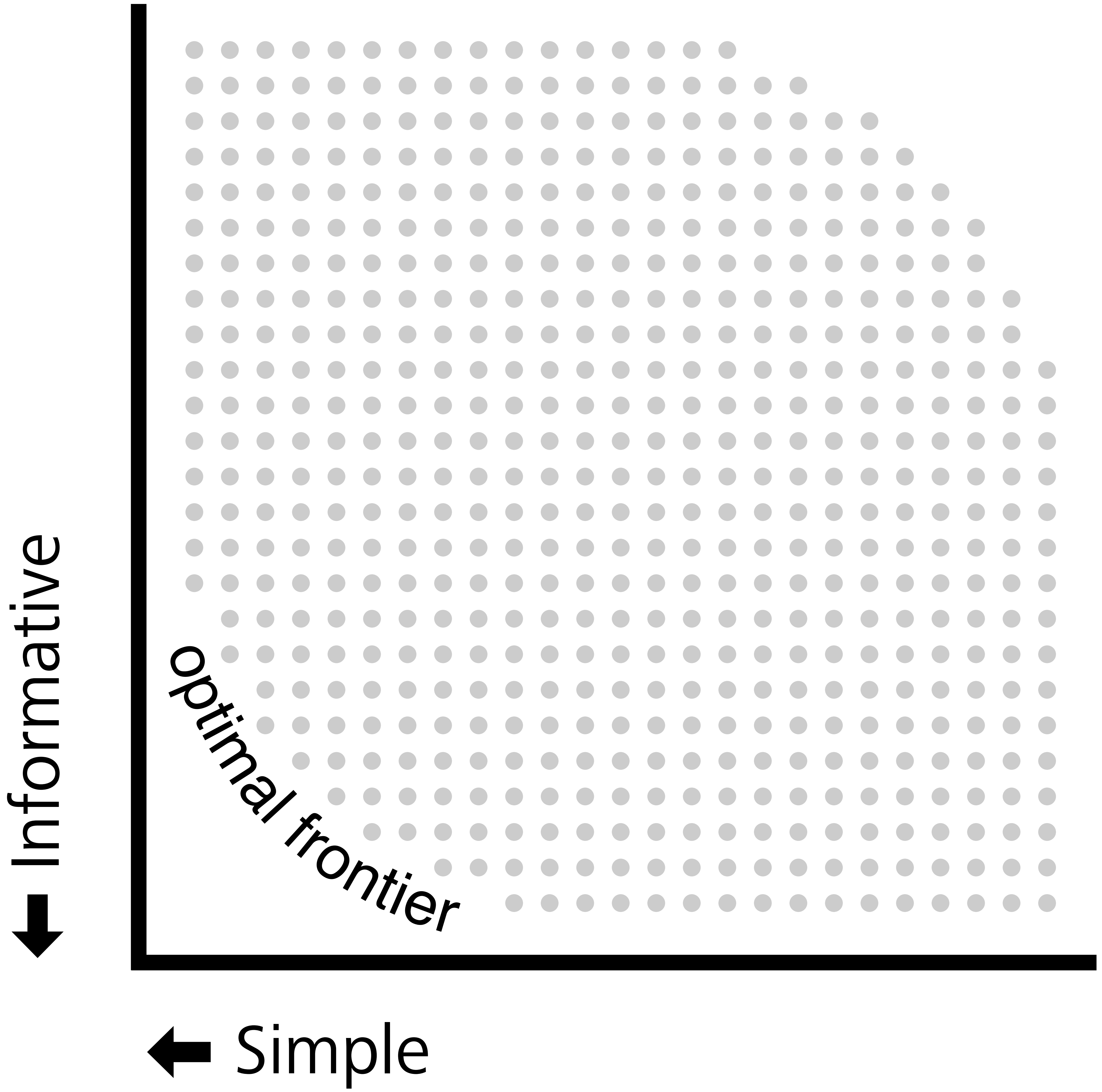
Kinship terms are simple and informative

Kemp & Regier (2012)

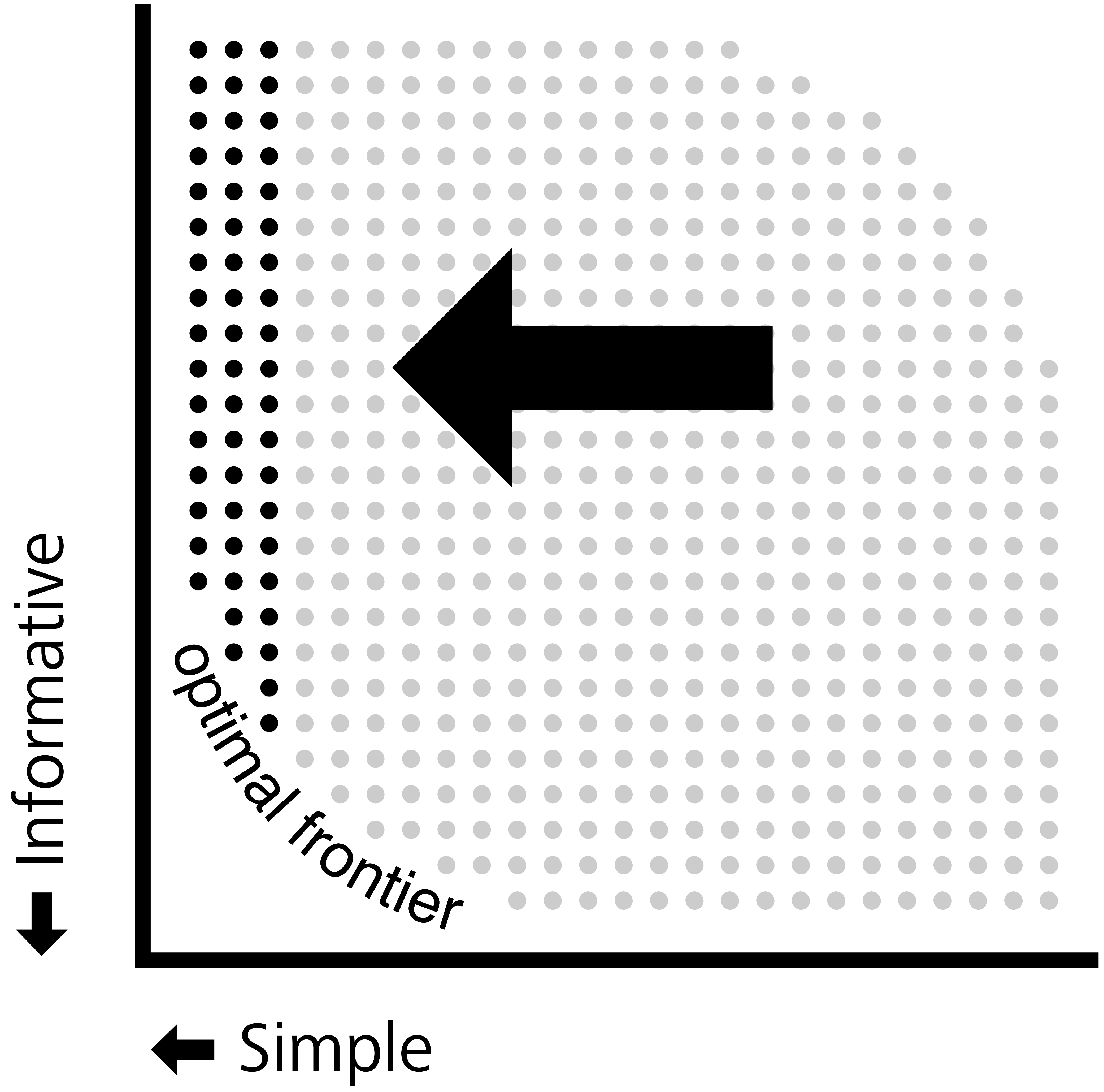




Pressures operating in simplicity–informativeness space



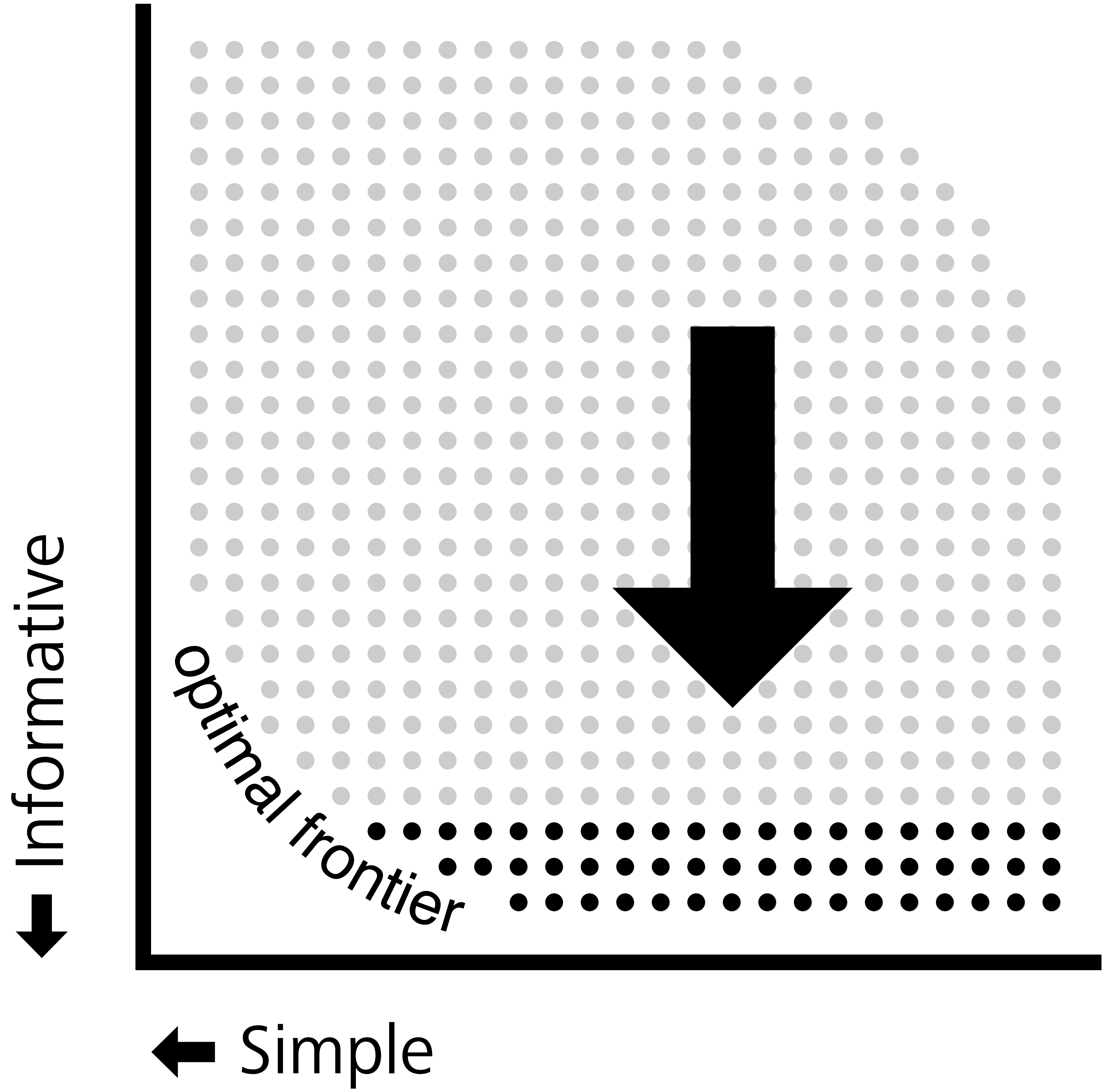
Pressures operating in simplicity–informativeness space



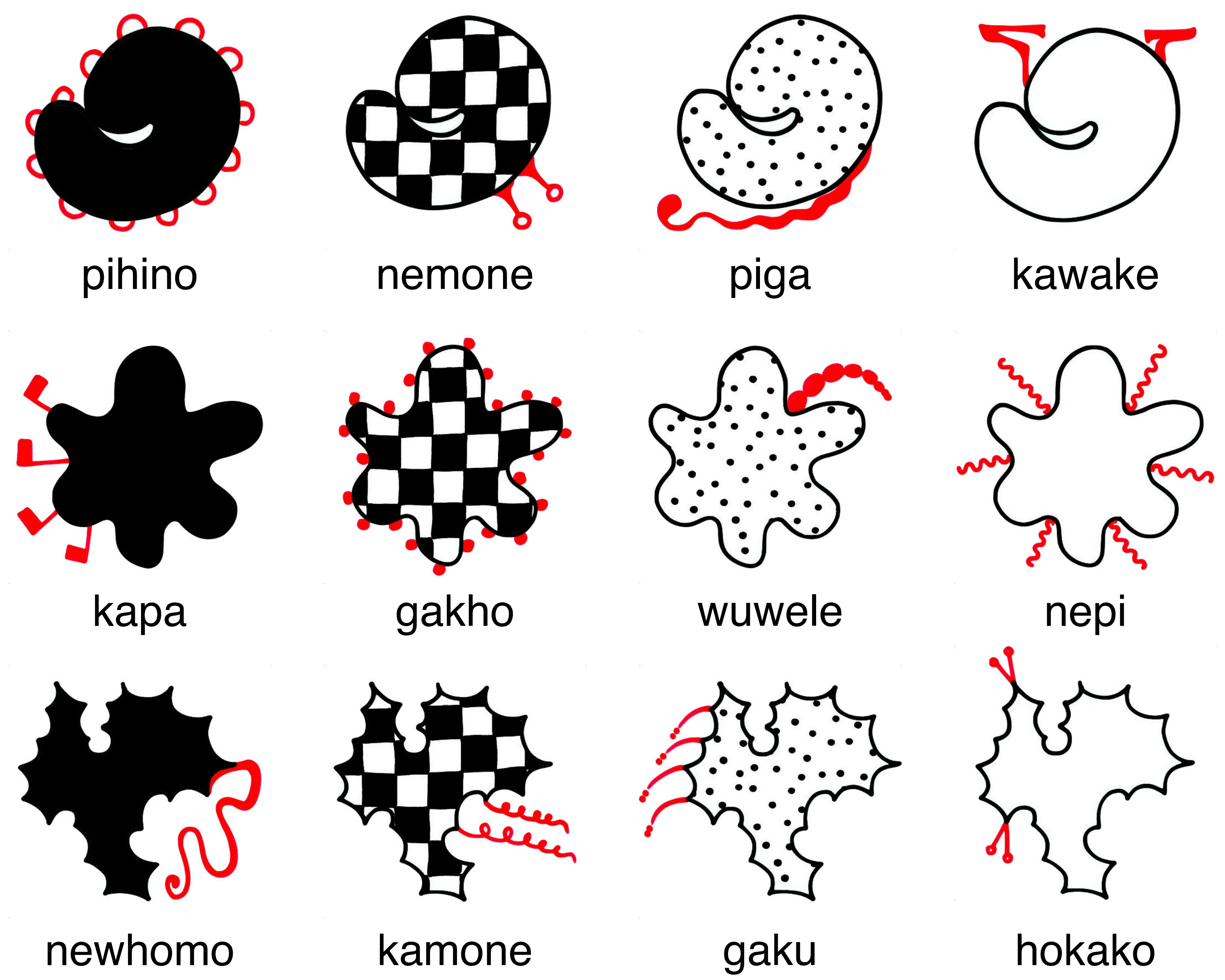
Learning exerts pressure for simplicity

Kirby, Cornish, & Smith (2008)

Pressures operating in simplicity–informativeness space

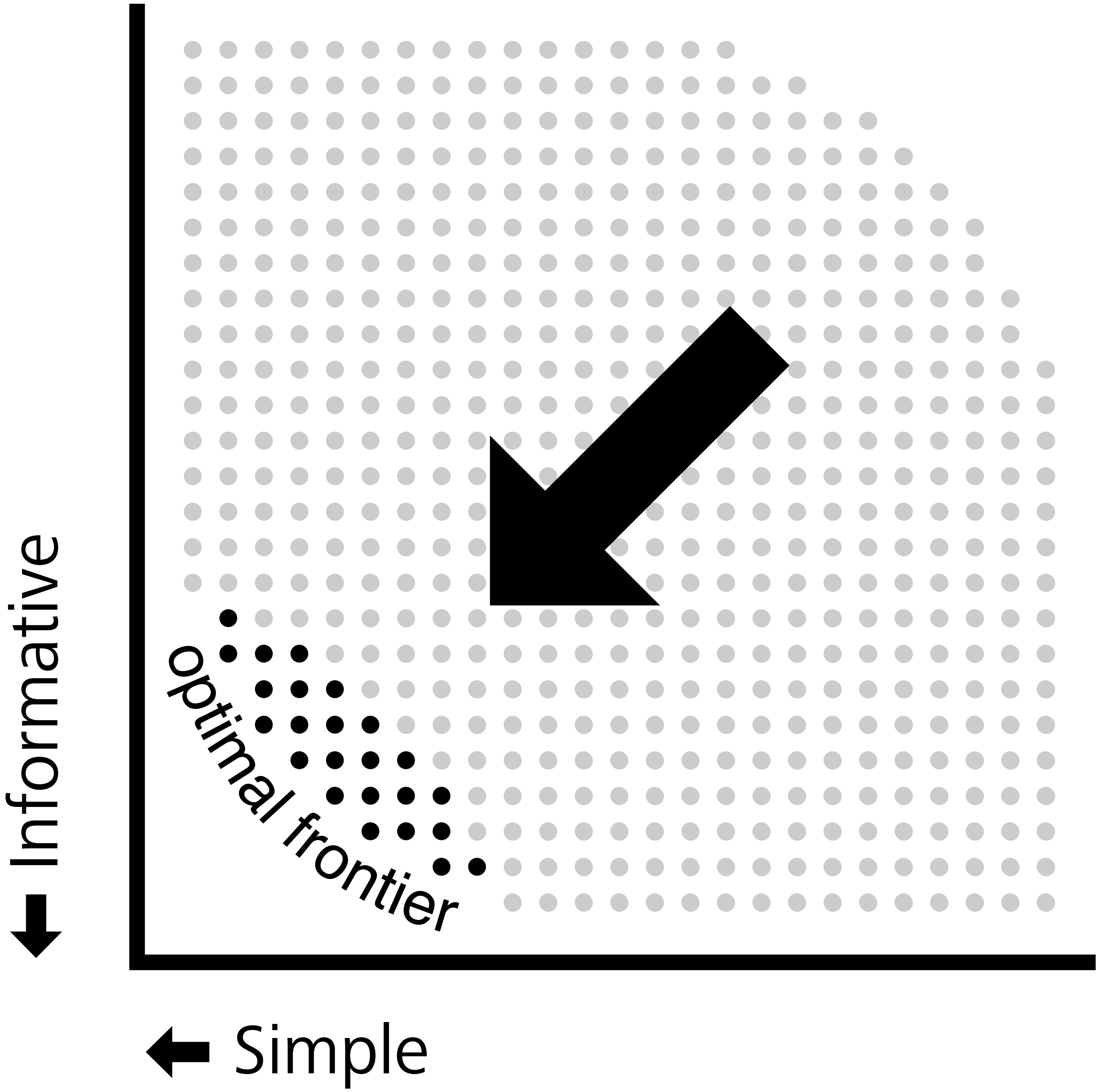


Communication exerts pressure for informativeness

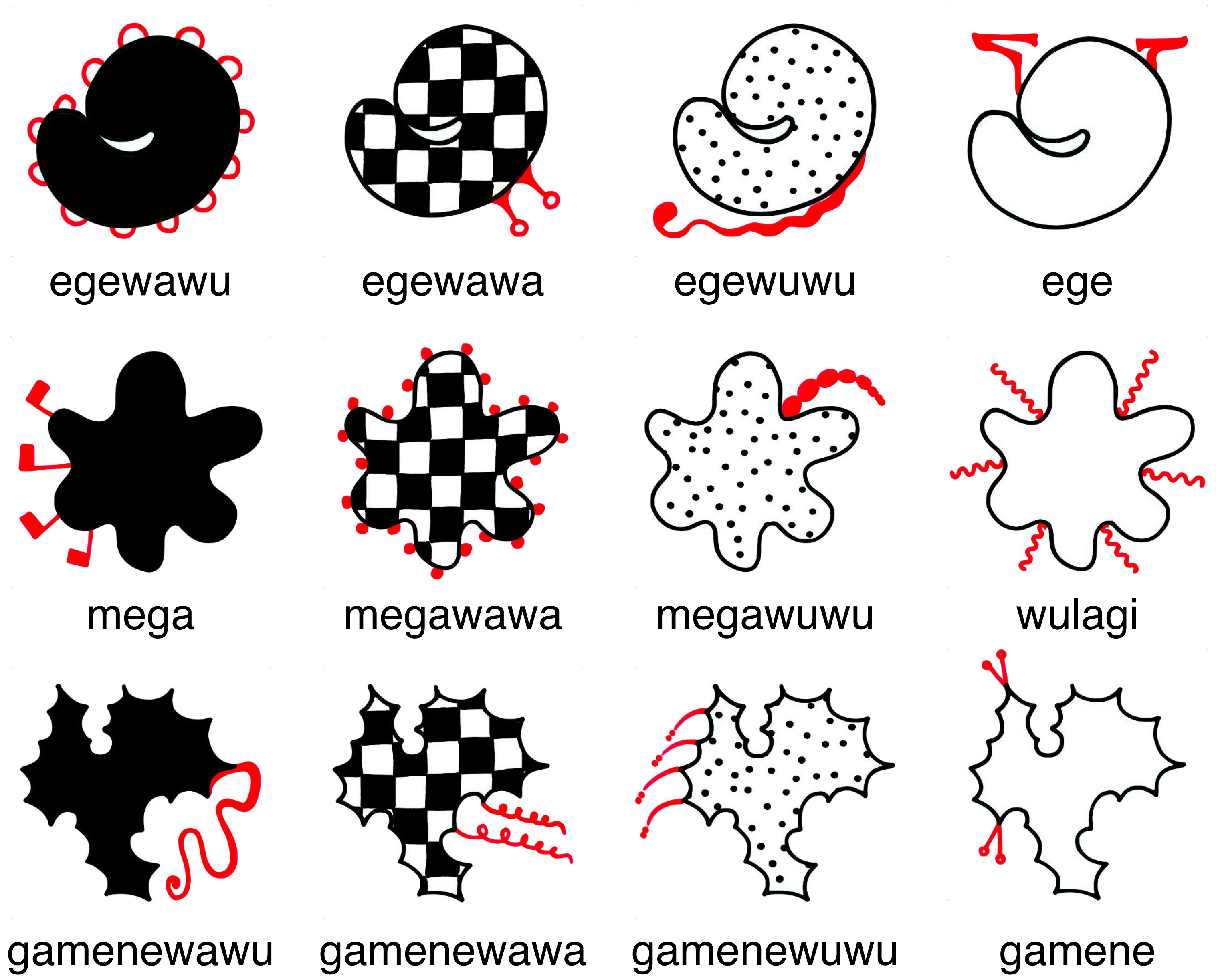


Kirby, Tamariz, Cornish, & Smith (2015)

Pressures operating in simplicity–informativeness space

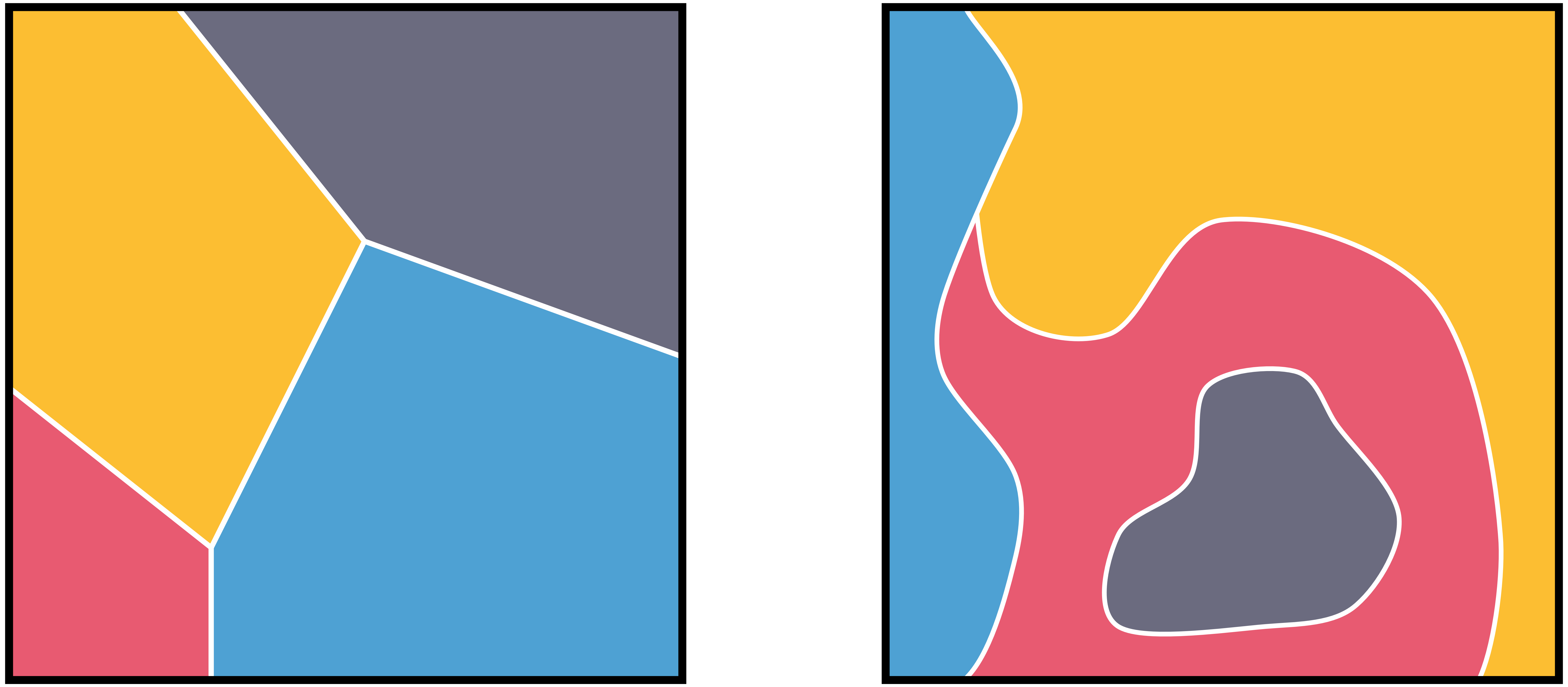


Learning + Communication
exerts pressure for simplicity and informativeness

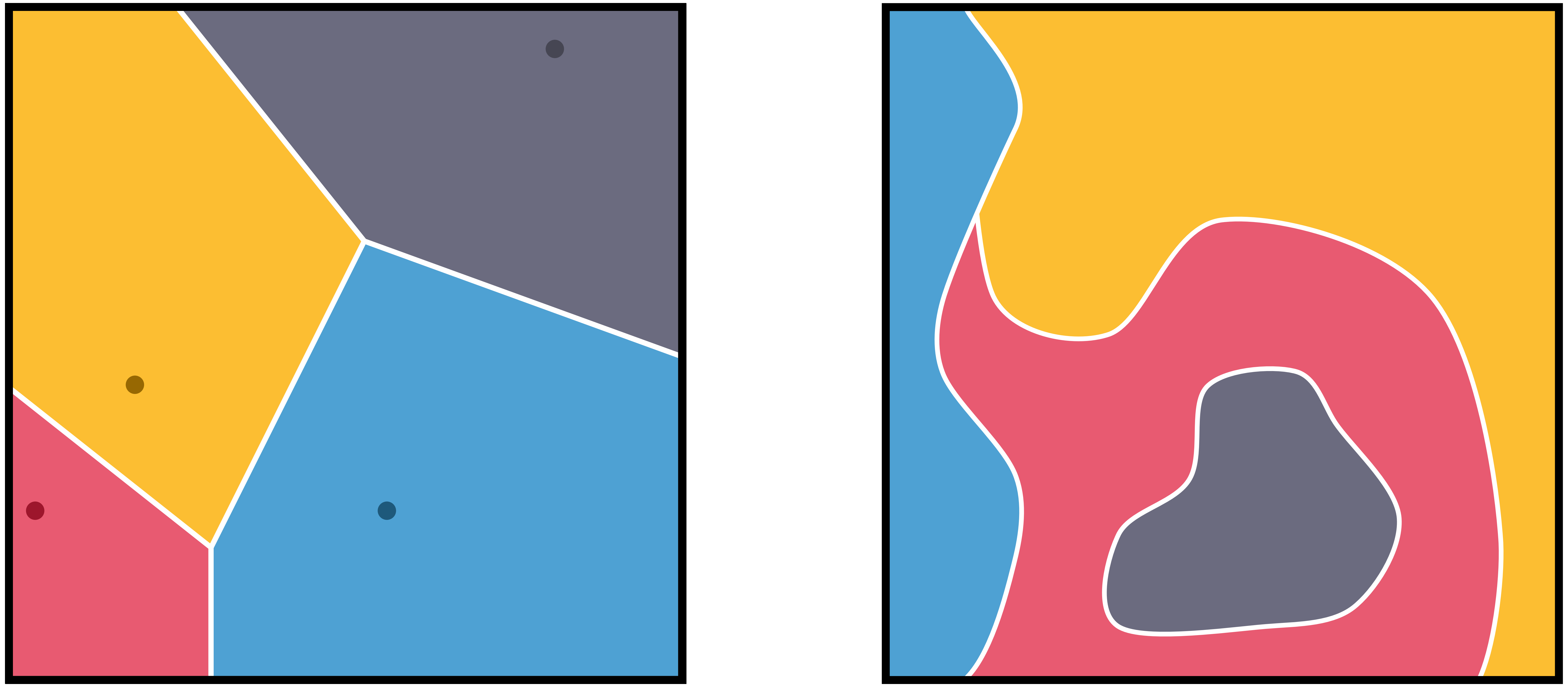


Kirby, Tamariz, Cornish, & Smith (2015)

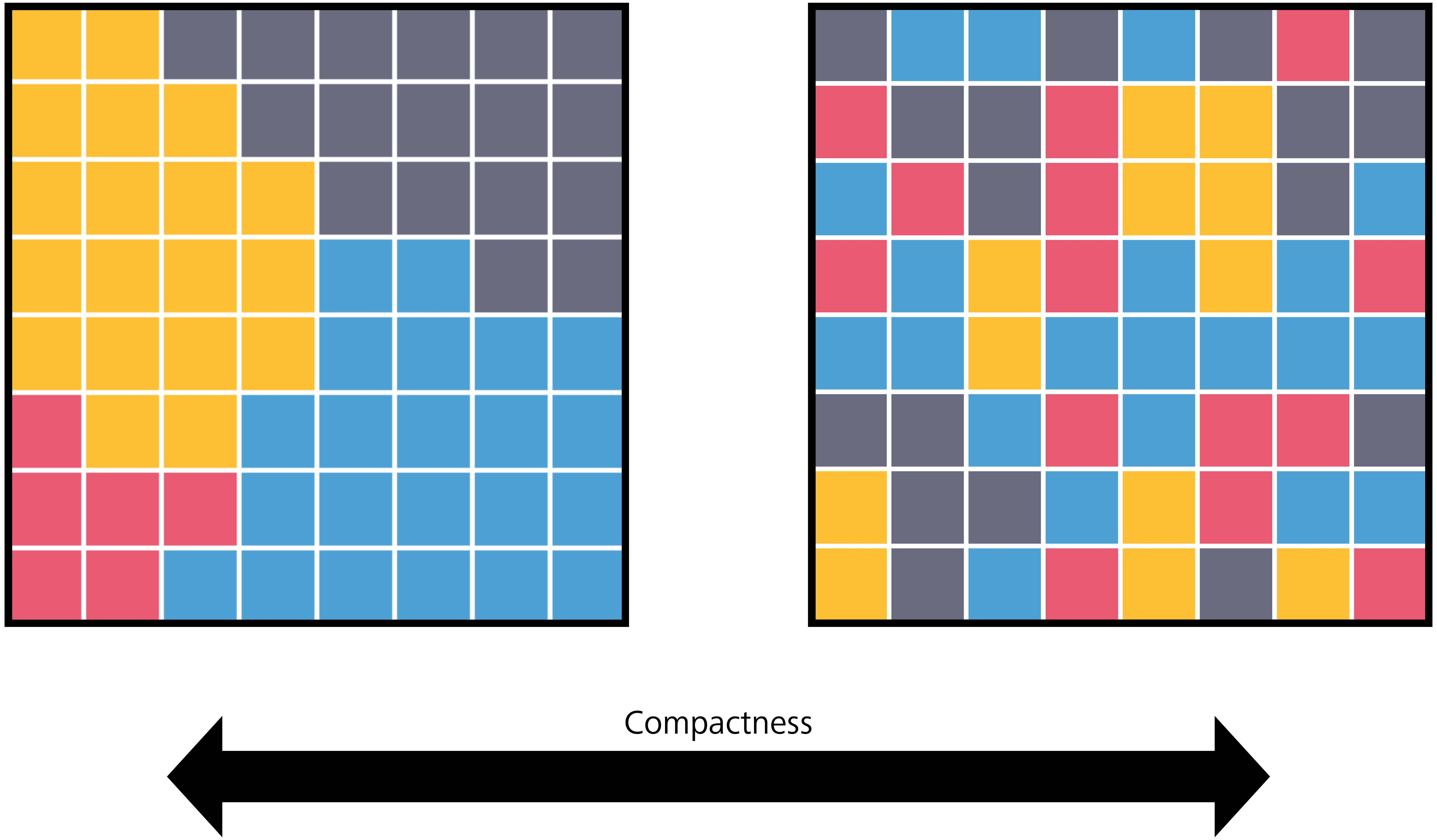
Semantic category systems



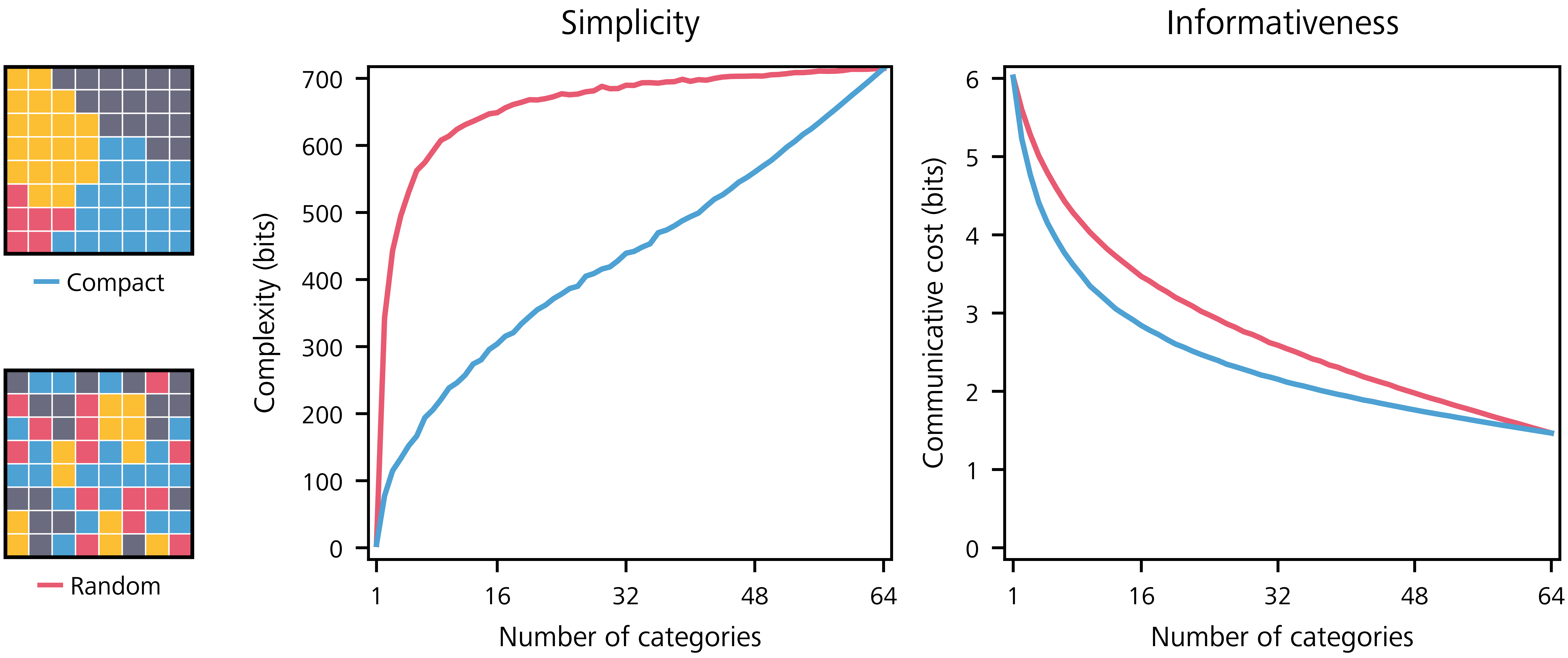
Semantic category systems



Semantic category systems



Simplicity and informativeness of semantic category systems



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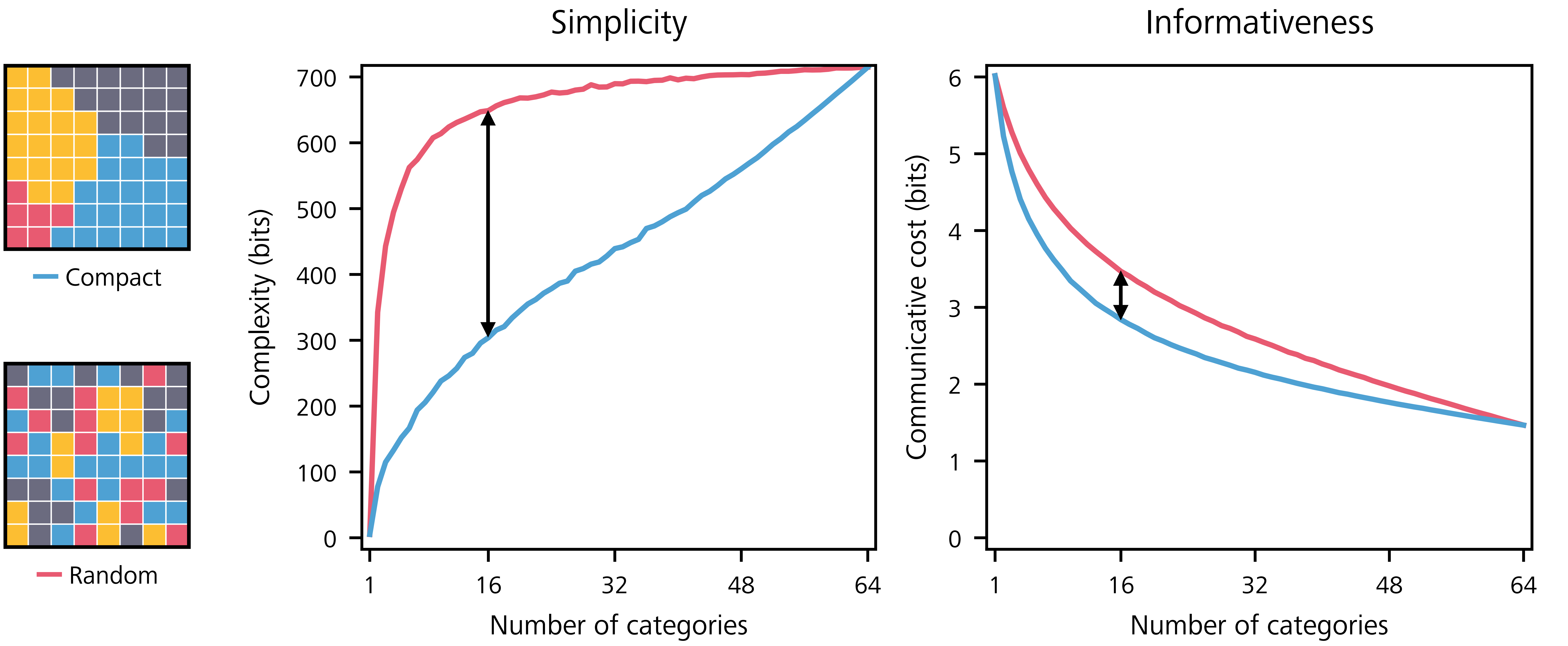
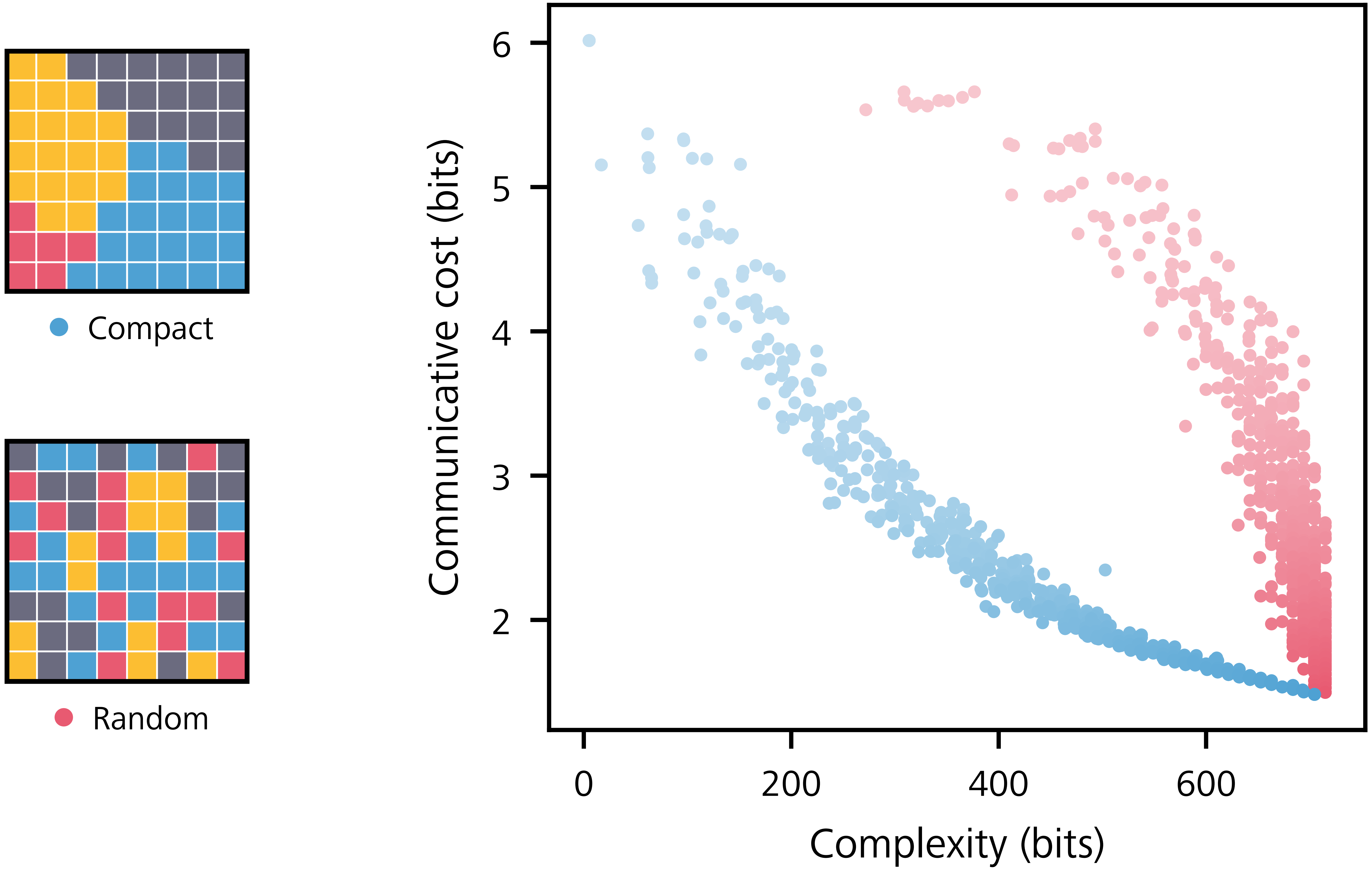


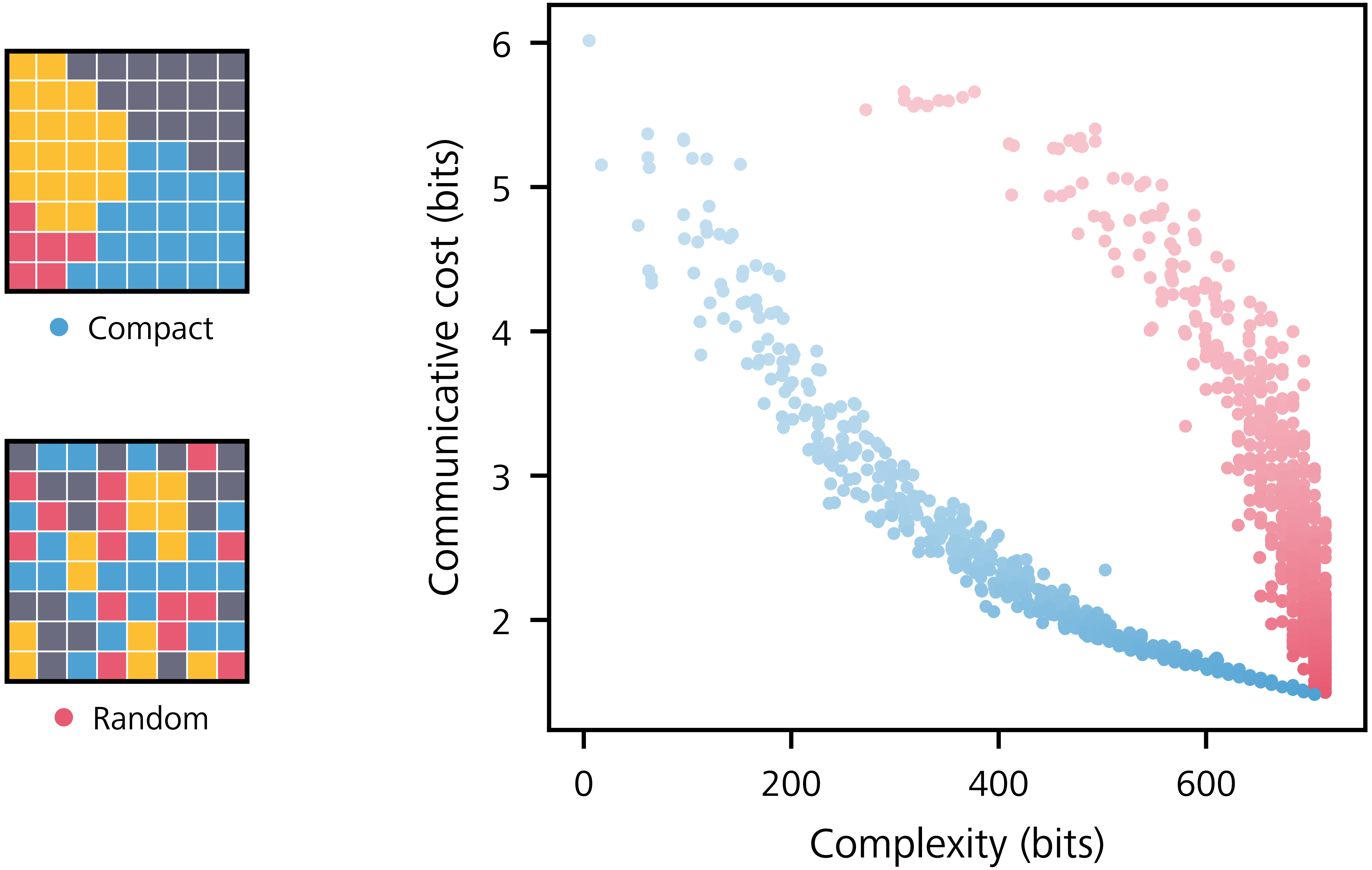
Hallmark features of simple and informative category systems



Simplicity pressure from induction favours
Few categories
Compactness

Informativeness pressure from interaction favours
Many categories
Compactness

Hallmark features of simple and informative category systems



Simplicity pressure from induction favours
Few categories
Compactness

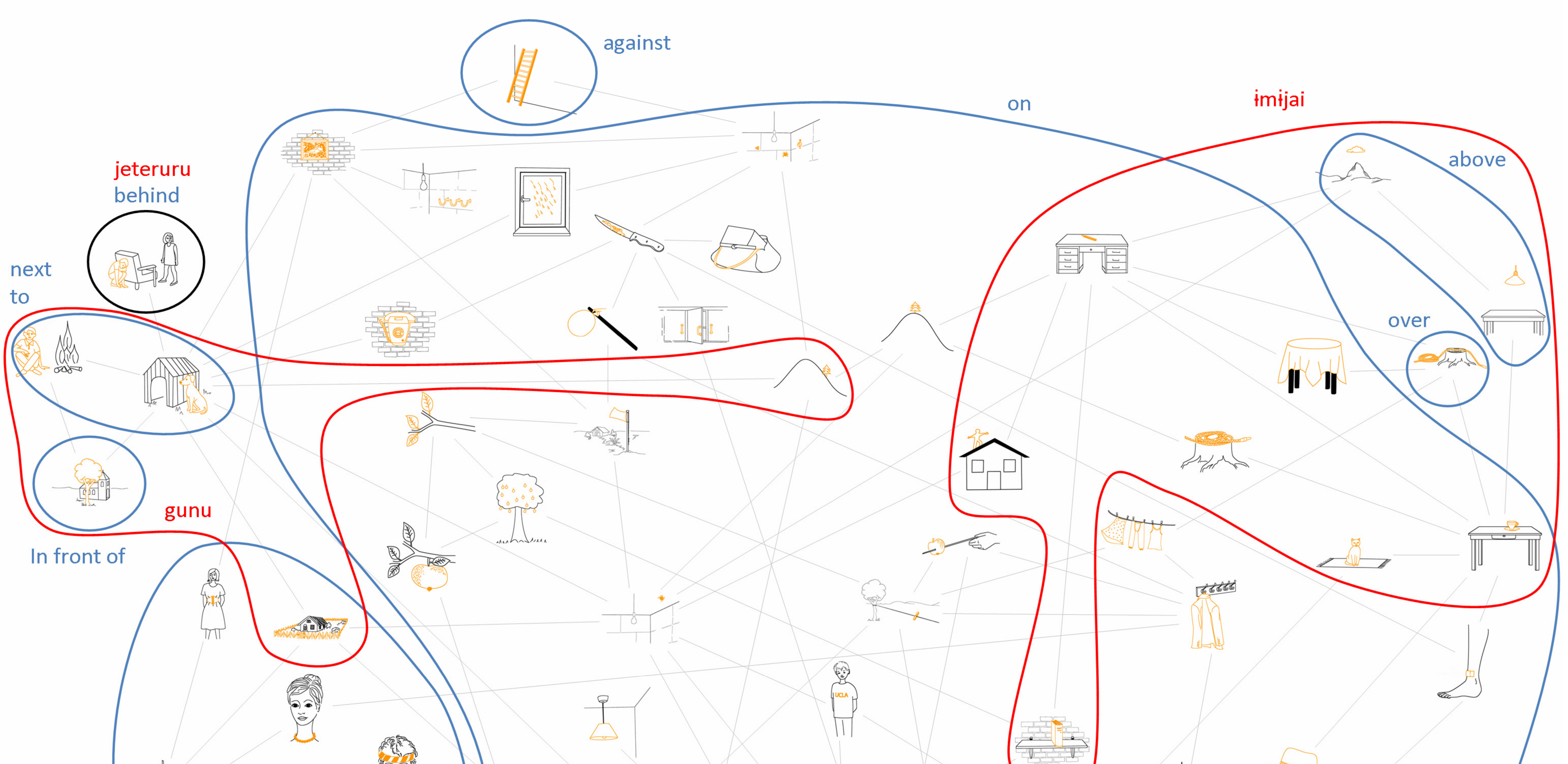
Informativeness pressure from interaction favours
Many categories
Compactness

Are semantic categories compact because of simplicity or informativeness?

Part 2

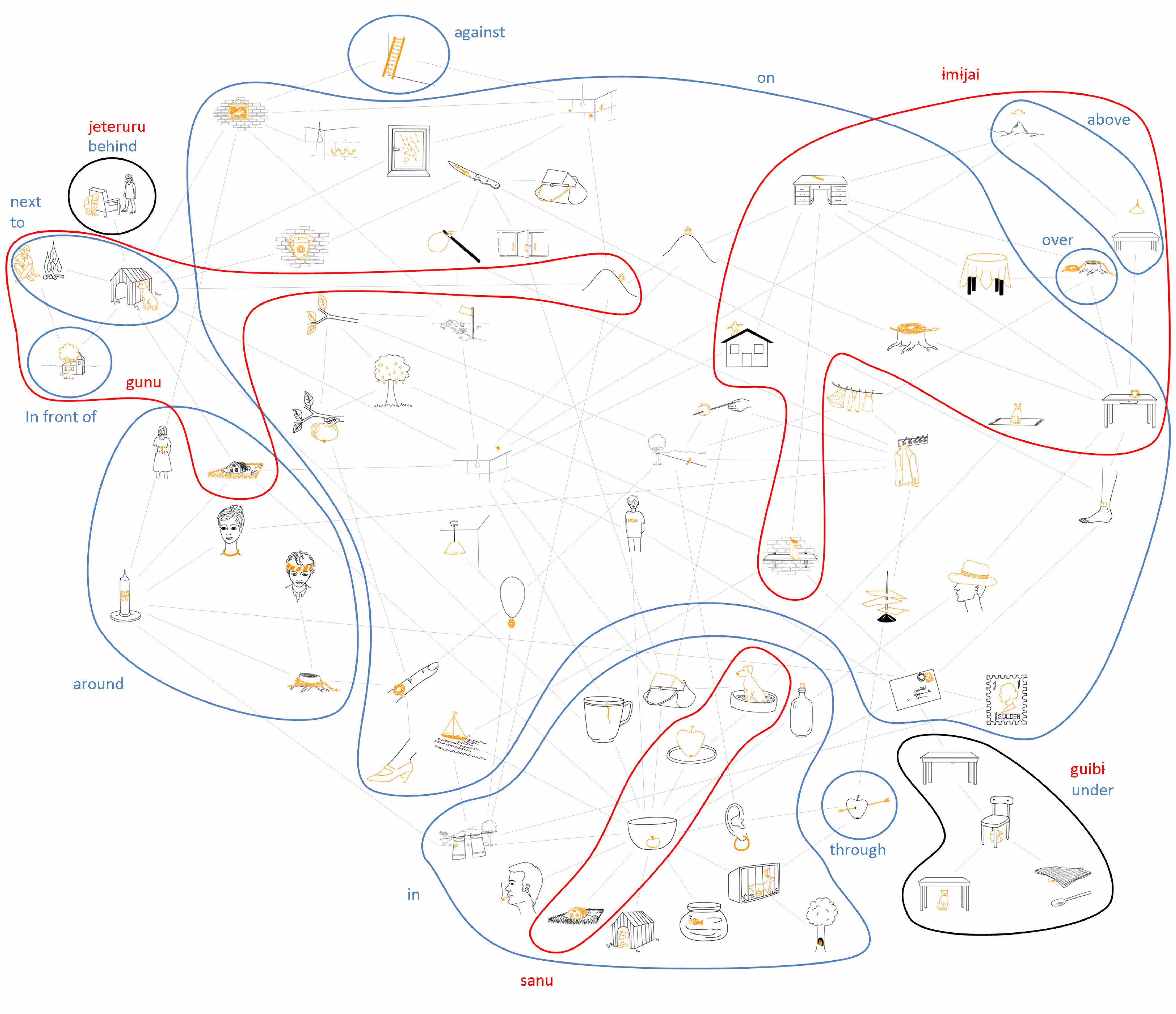
Can iterated learning give rise to informative languages?

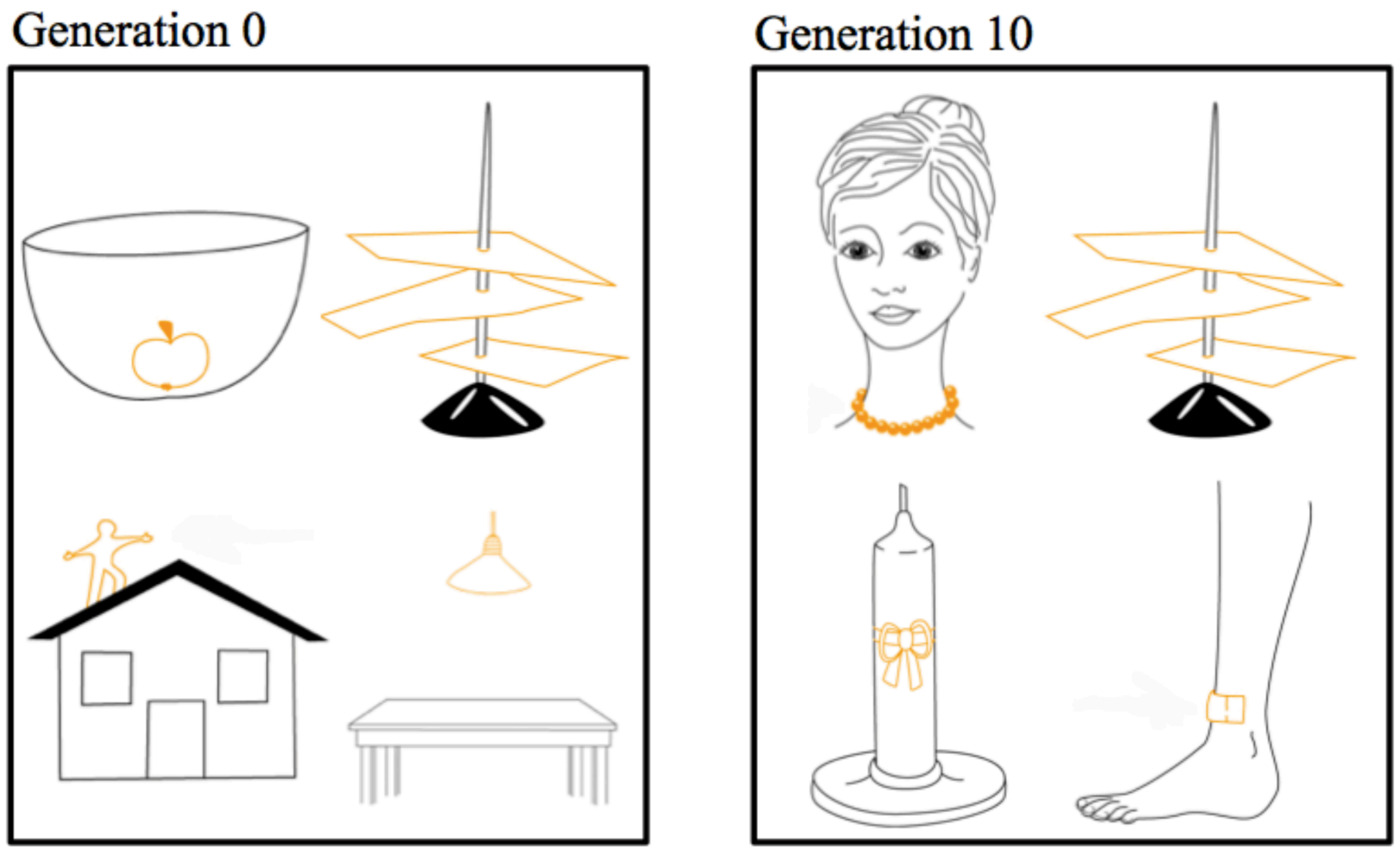
Carstensen, Xu, Smith, & Regier (2015)



Can iterated learning give rise to informative languages?

Carstensen, Xu, Smith, & Regier (2015)





Can iterated learning give rise to informative languages?

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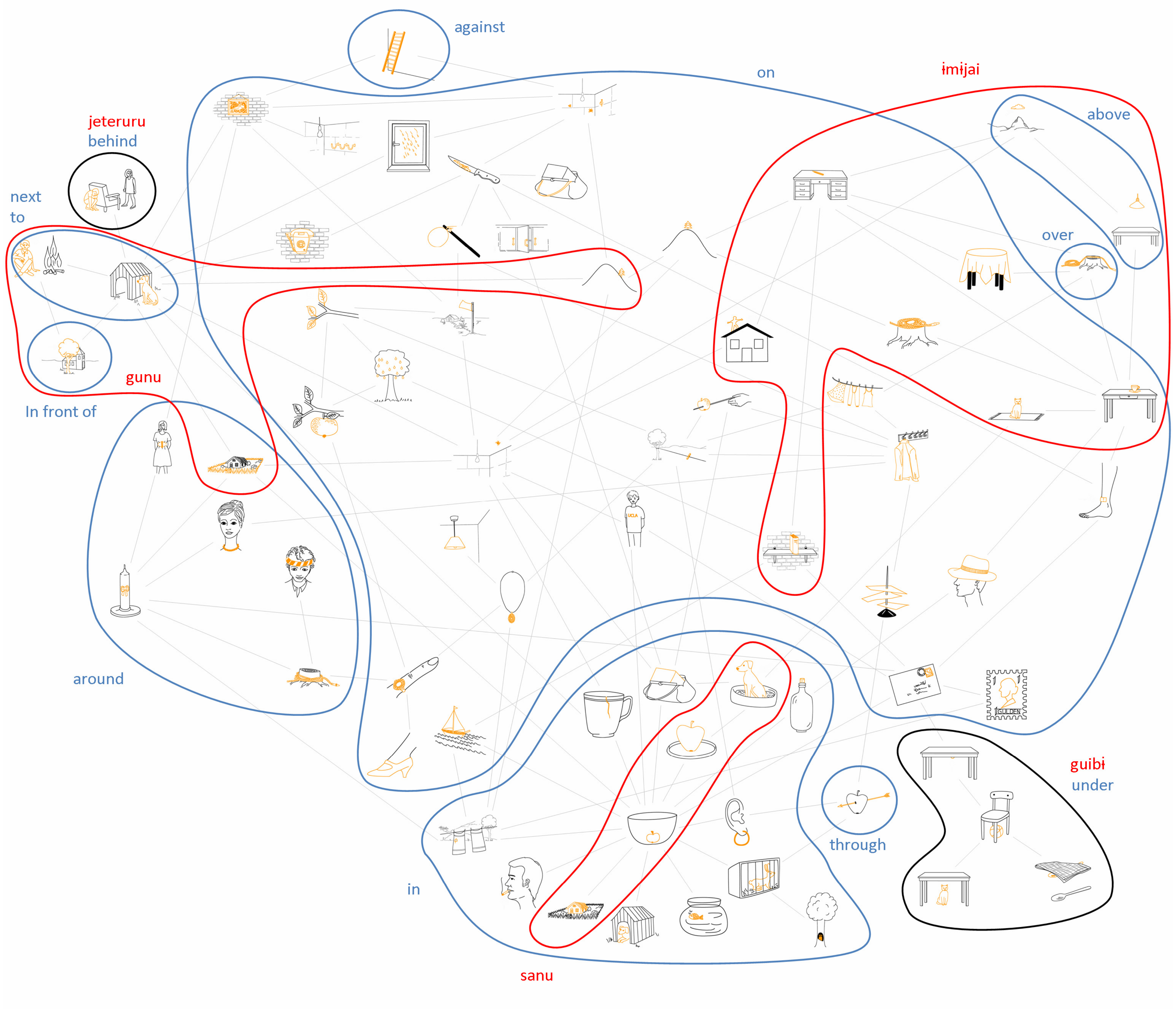
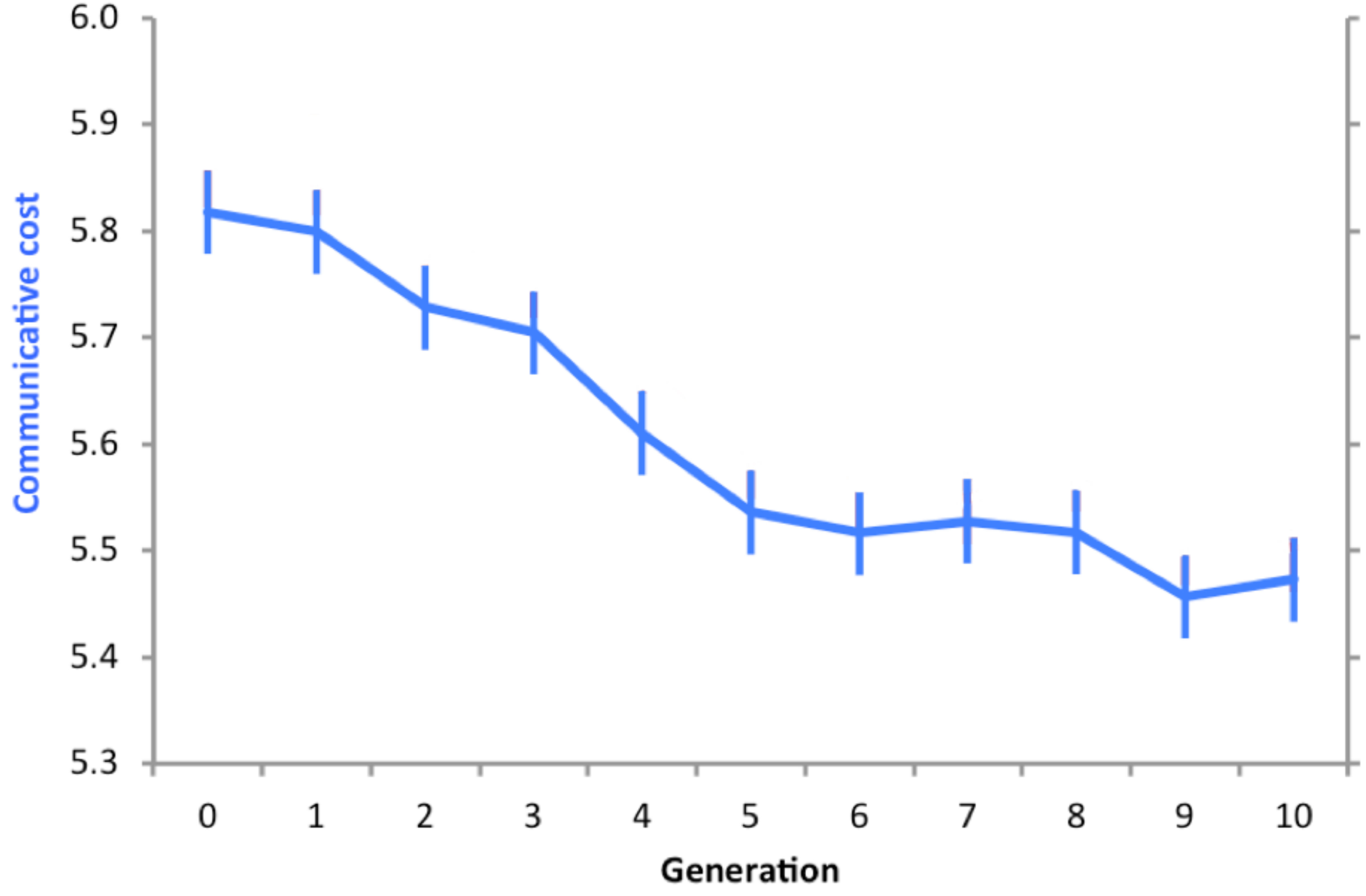
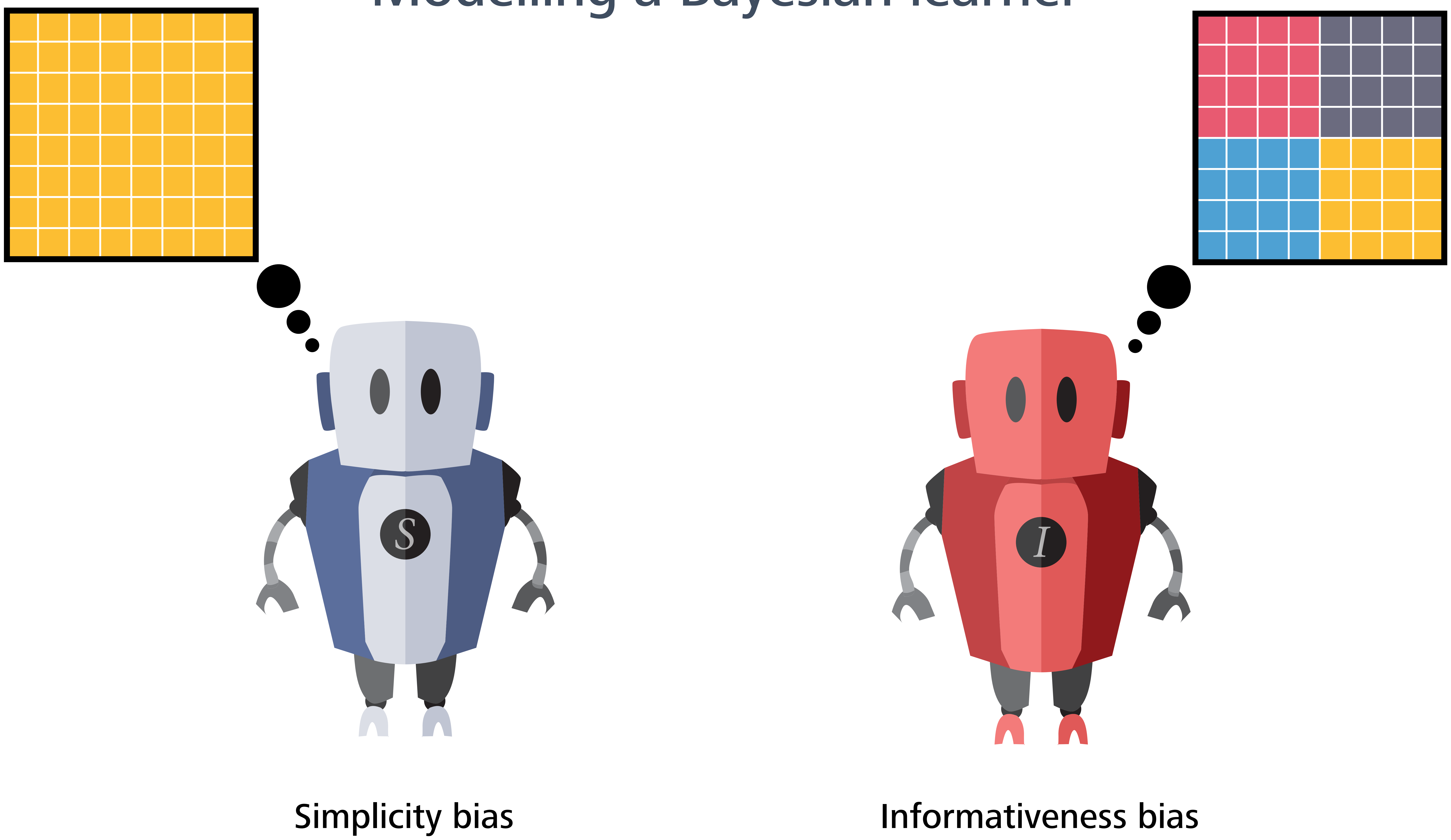
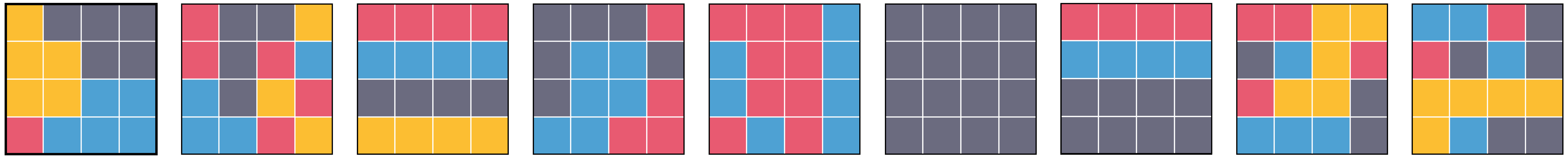




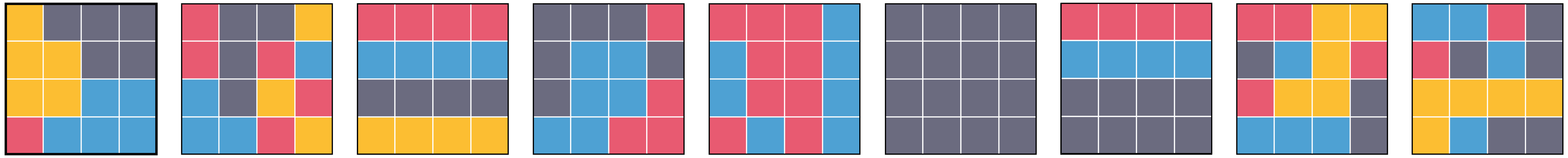
Modelling a Bayesian learner



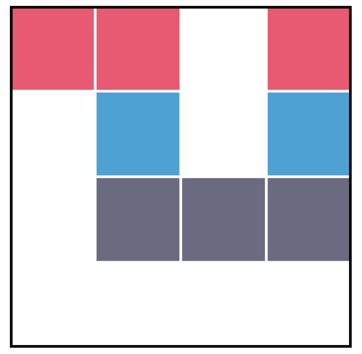
Bayesian inference

$\mathcal{L} = \{$  $\cdots \}$

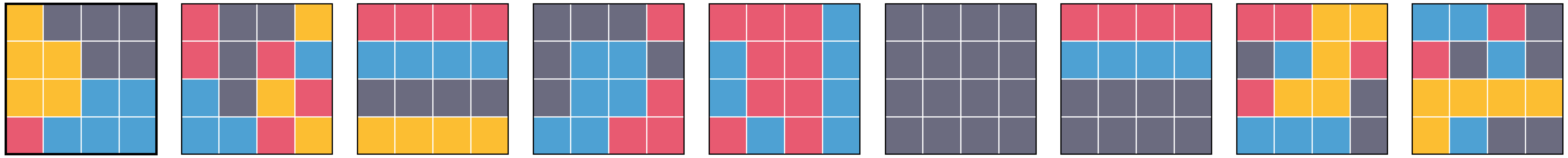
Bayesian inference

$\mathcal{L} = \{$  $\cdots\}$

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



Bayesian inference

$\mathcal{L} = \{$  $\cdots\}$

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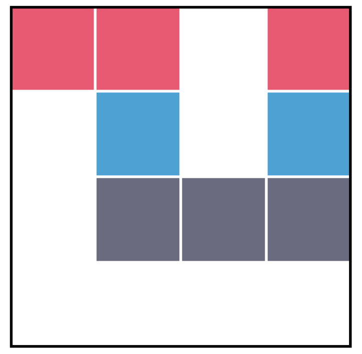
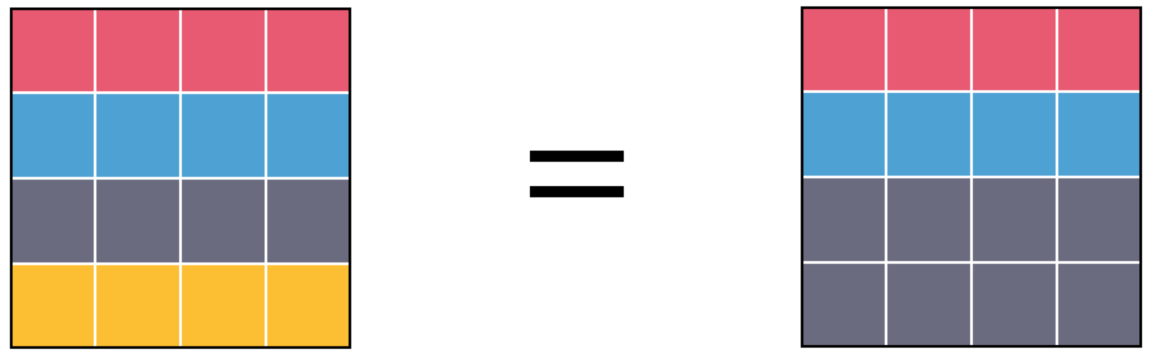


$$\text{likelihood}(D|L) = \prod_{\langle m,s\rangle} P(s|L,m)$$



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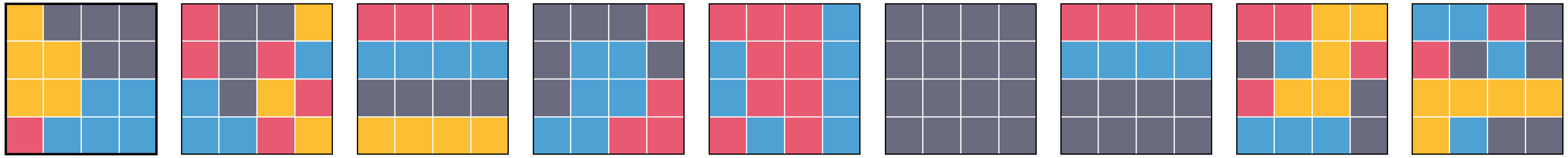
$\mathcal{L} = \{$  $\cdots\}$

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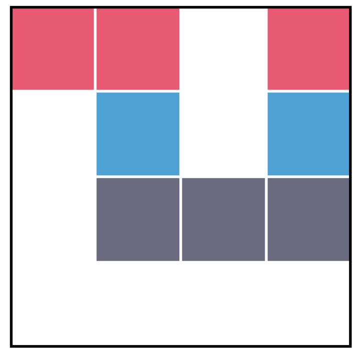

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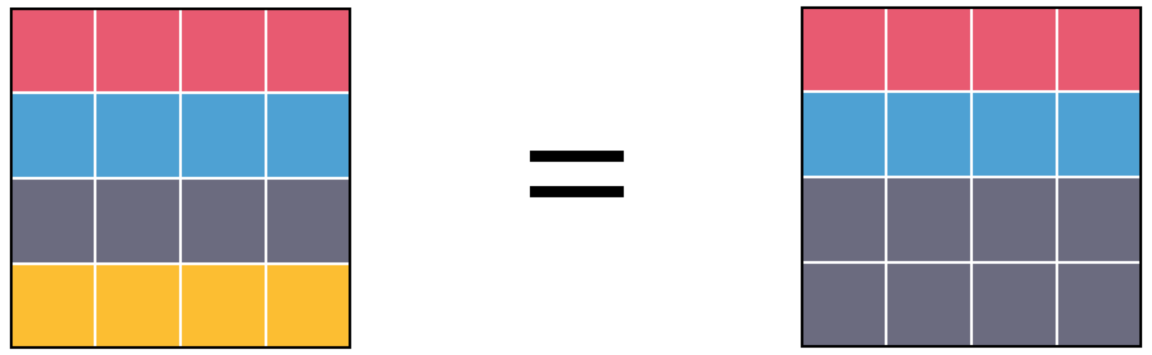
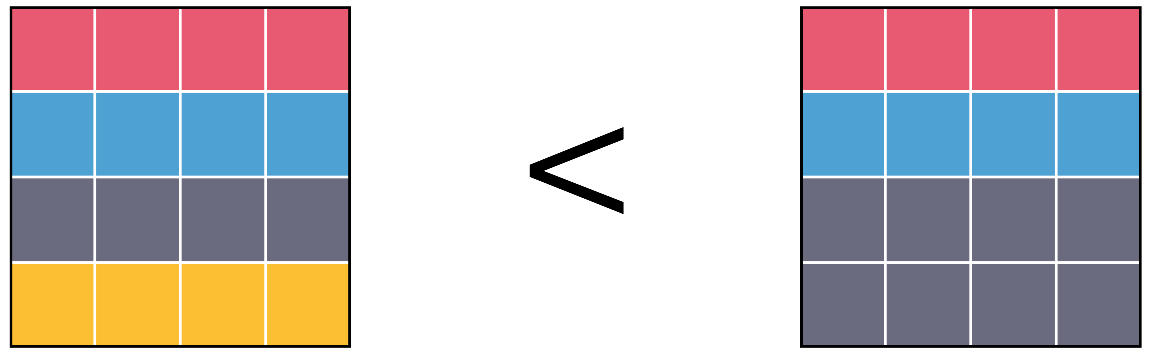
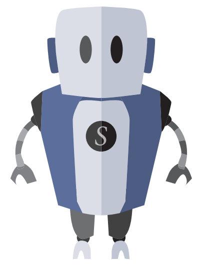
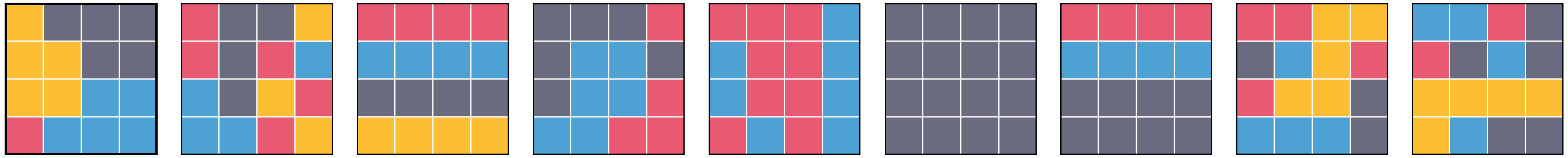






$$\text{prior}(L) \propto 2^{-\text{complexity}(L)}$$

Bayesian inference

$\mathcal{L} = \{$  $\cdots\}$

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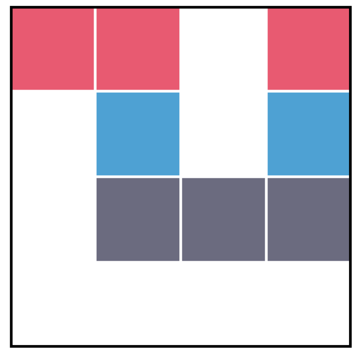
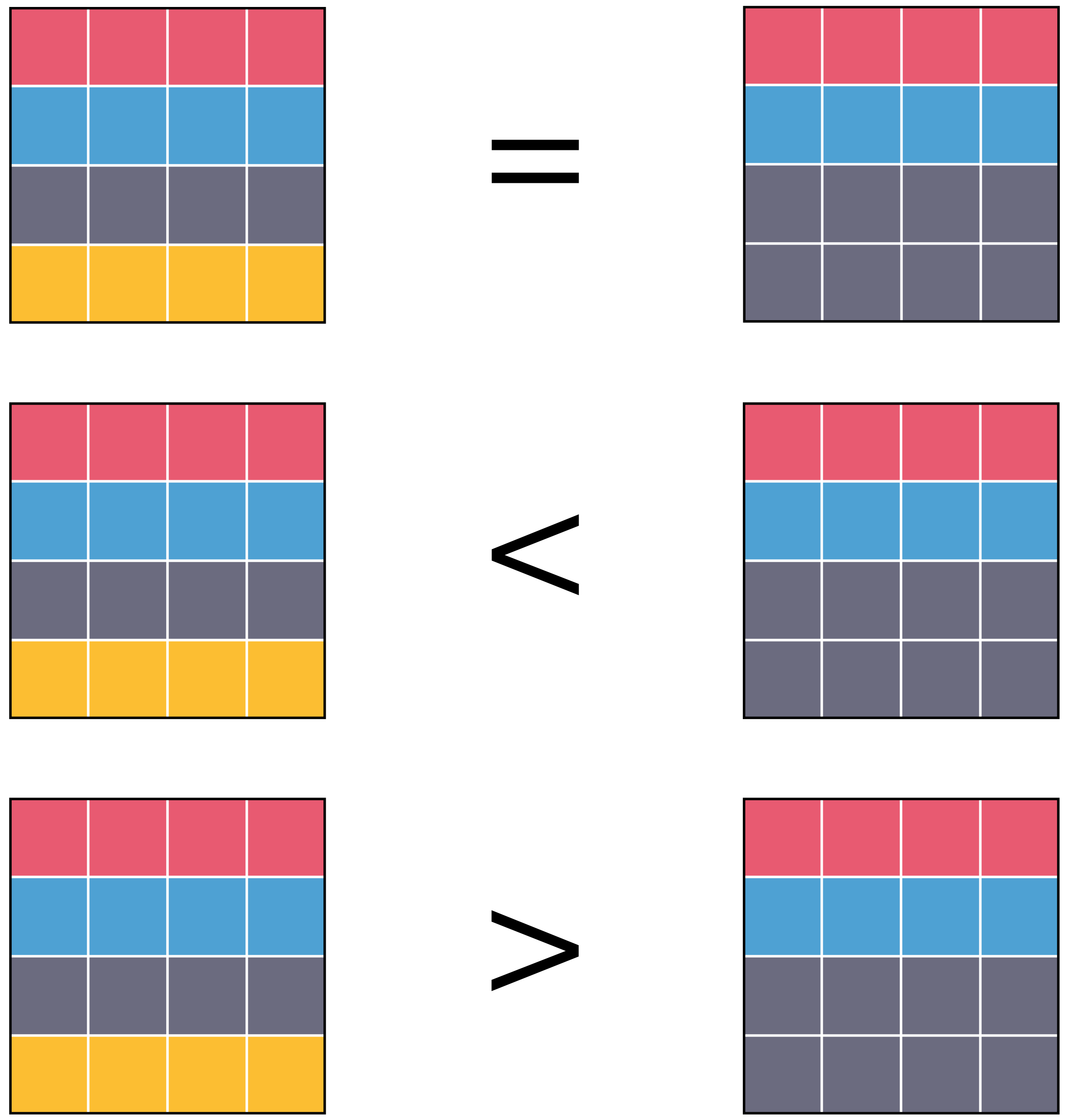
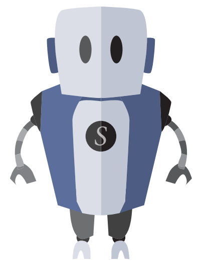
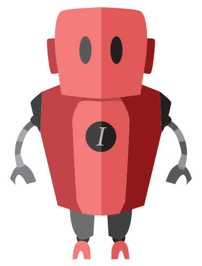


$$\text{likelihood}(D|L) = \prod_{\langle m,s \rangle} P(s|L,m)$$



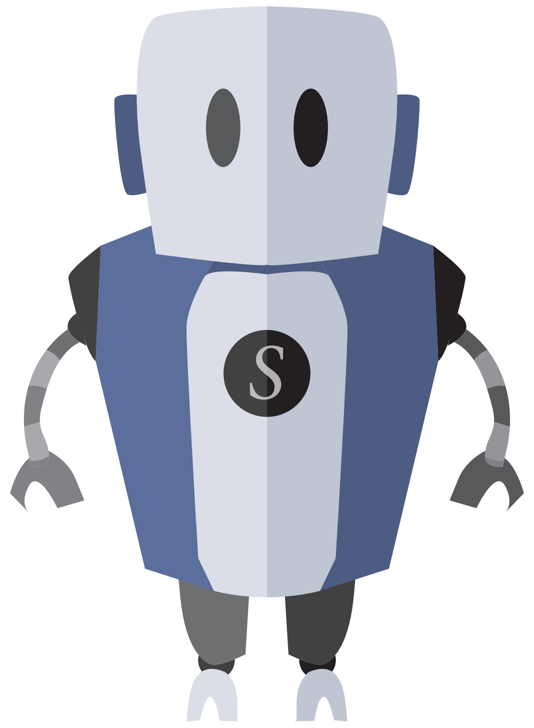
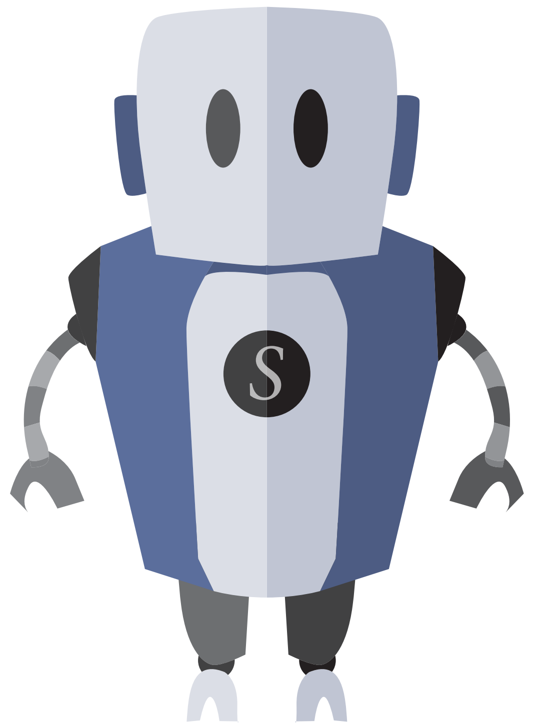
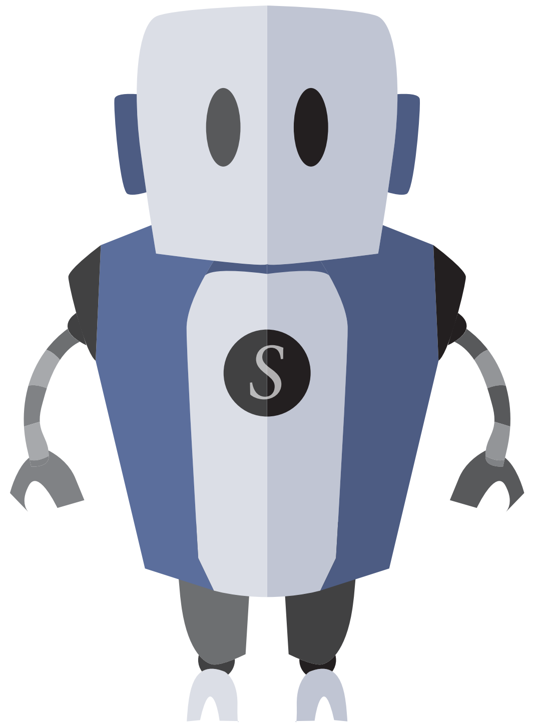


$\text{prior}(L) \propto 2^{-\text{complexity}(L)}$



$\text{prior}(L) \propto 2^{-\text{cost}(L)}$

Bayesian iterated learning under a **simplicity prior**

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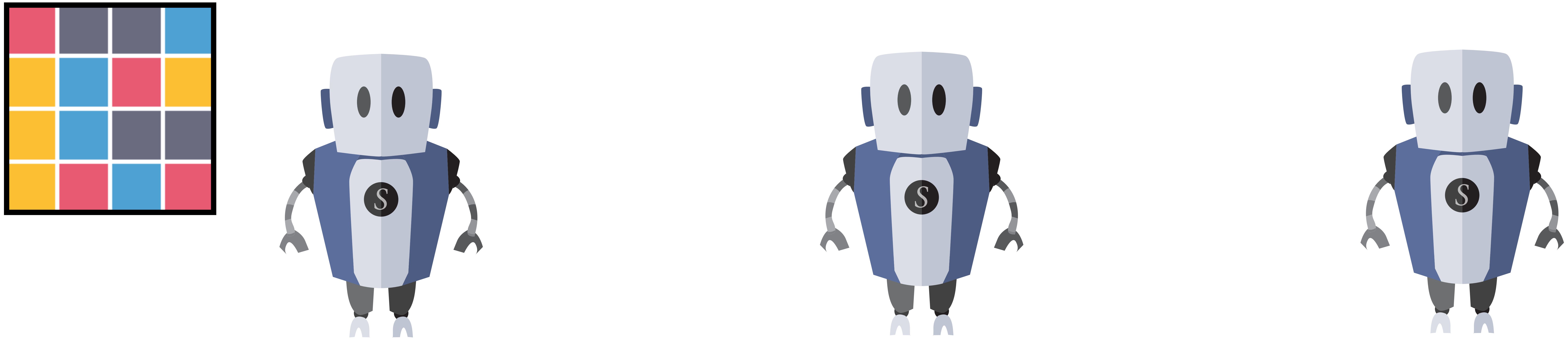

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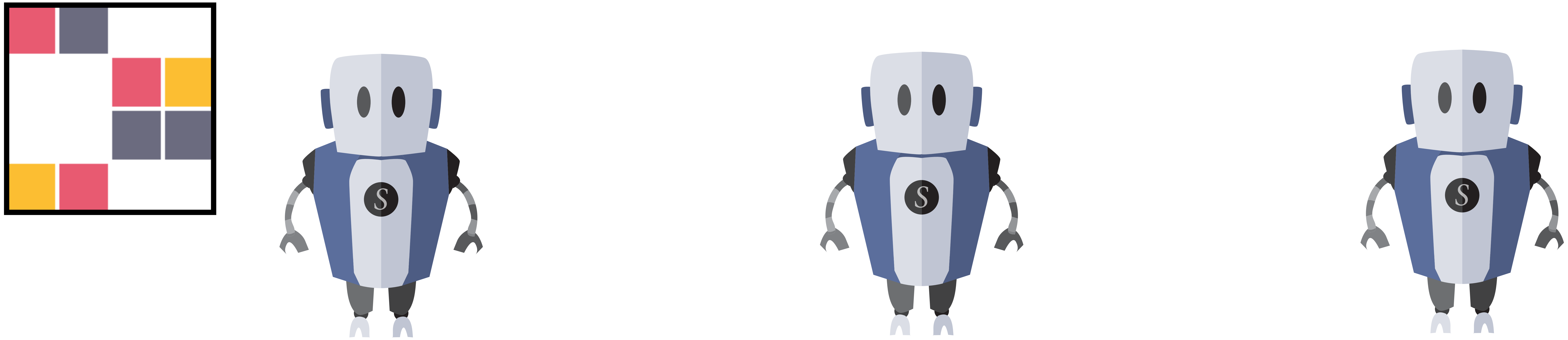

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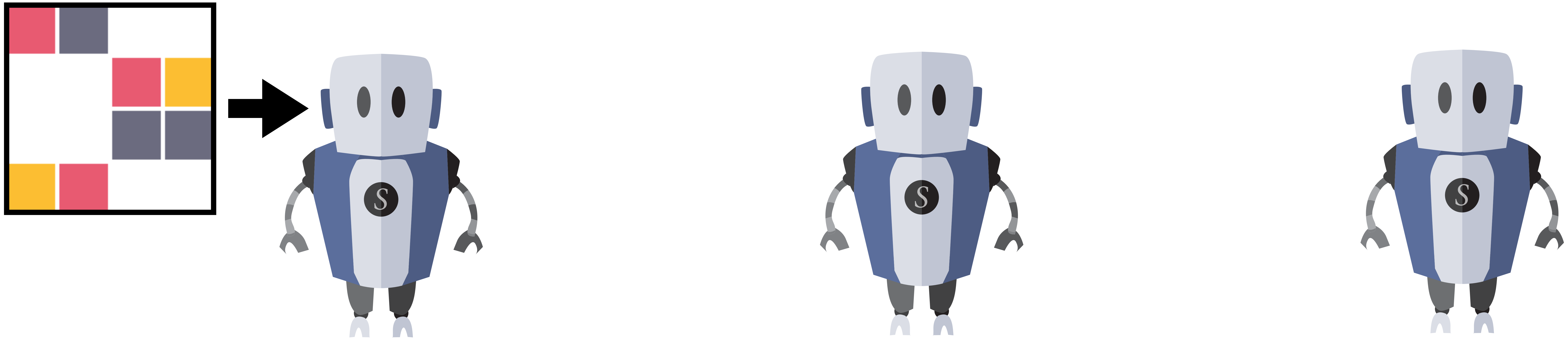

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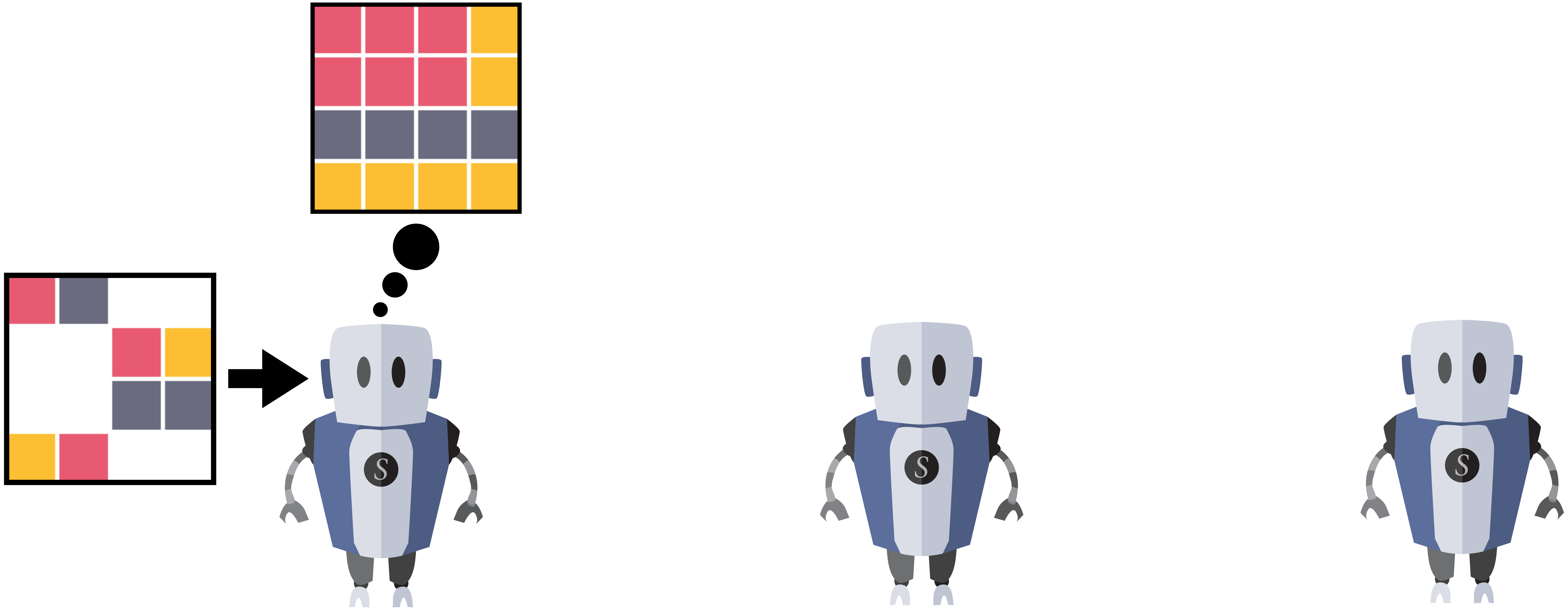

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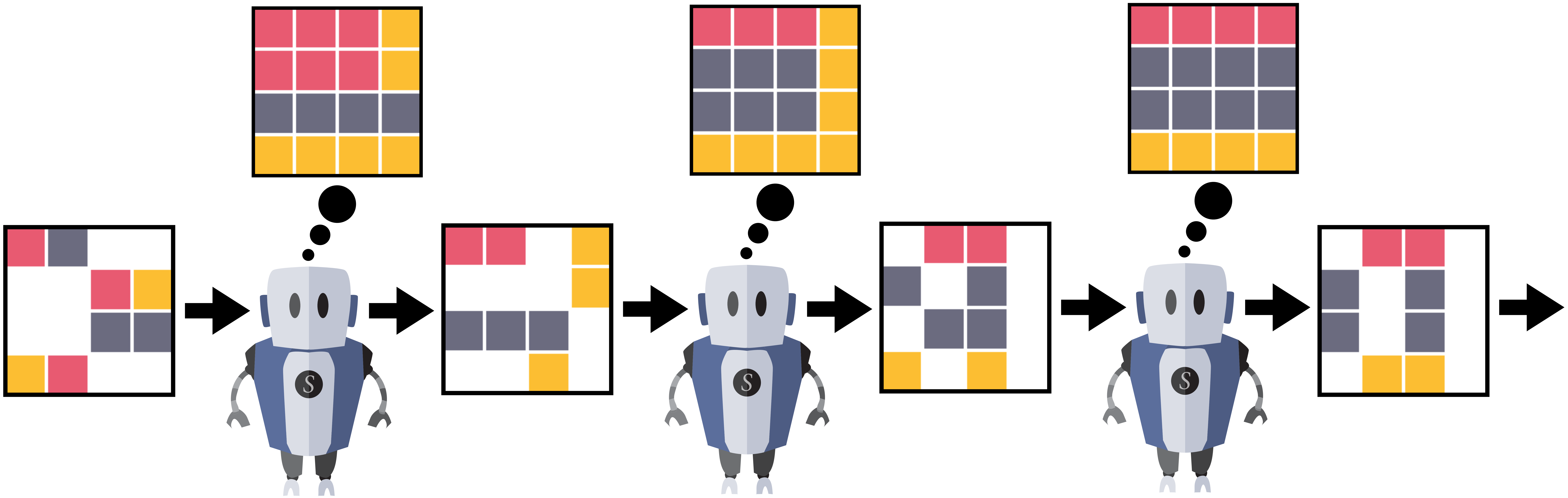
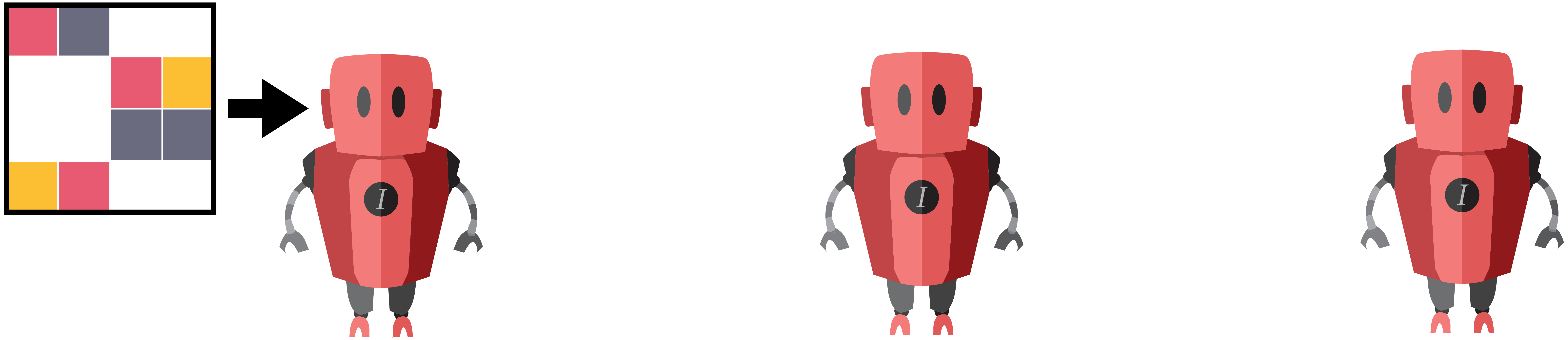
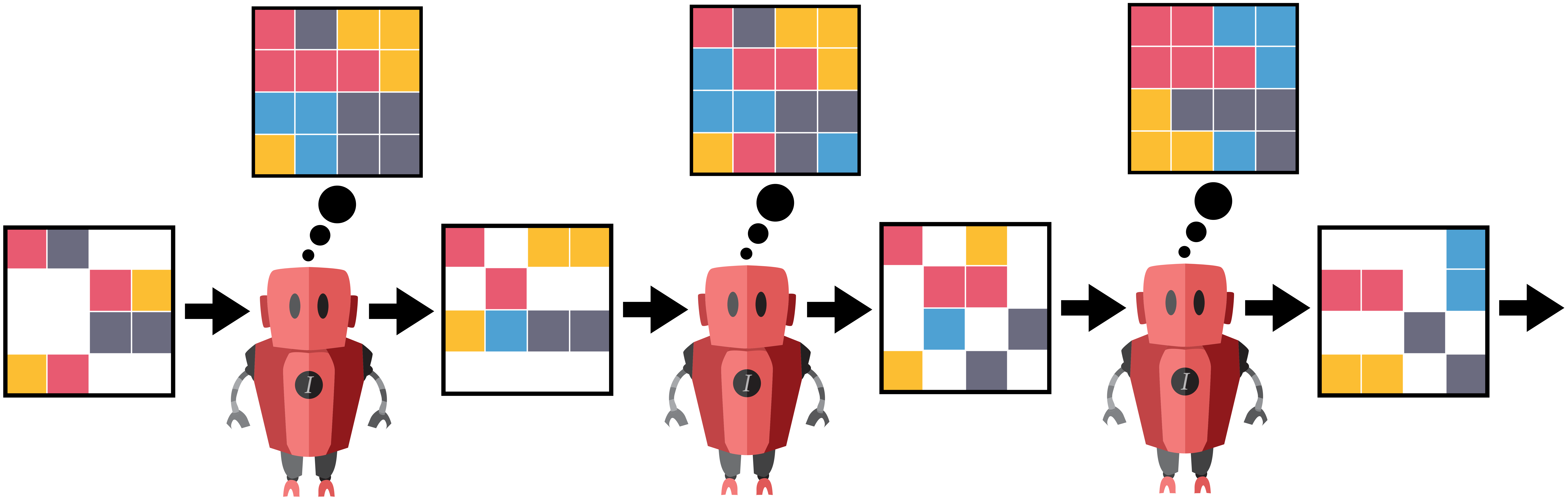


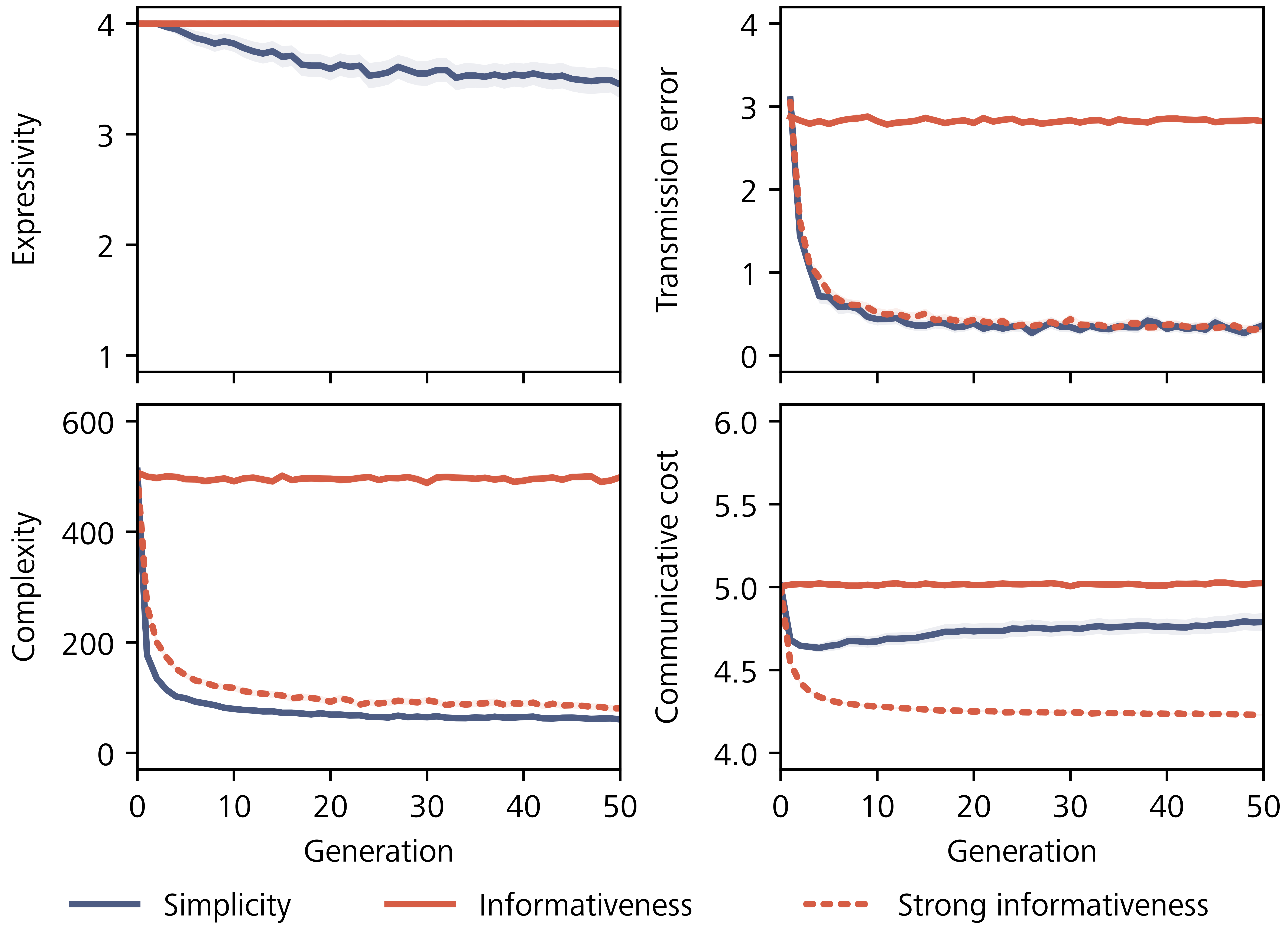
Bayesian iterated learning under an **informativeness prior**



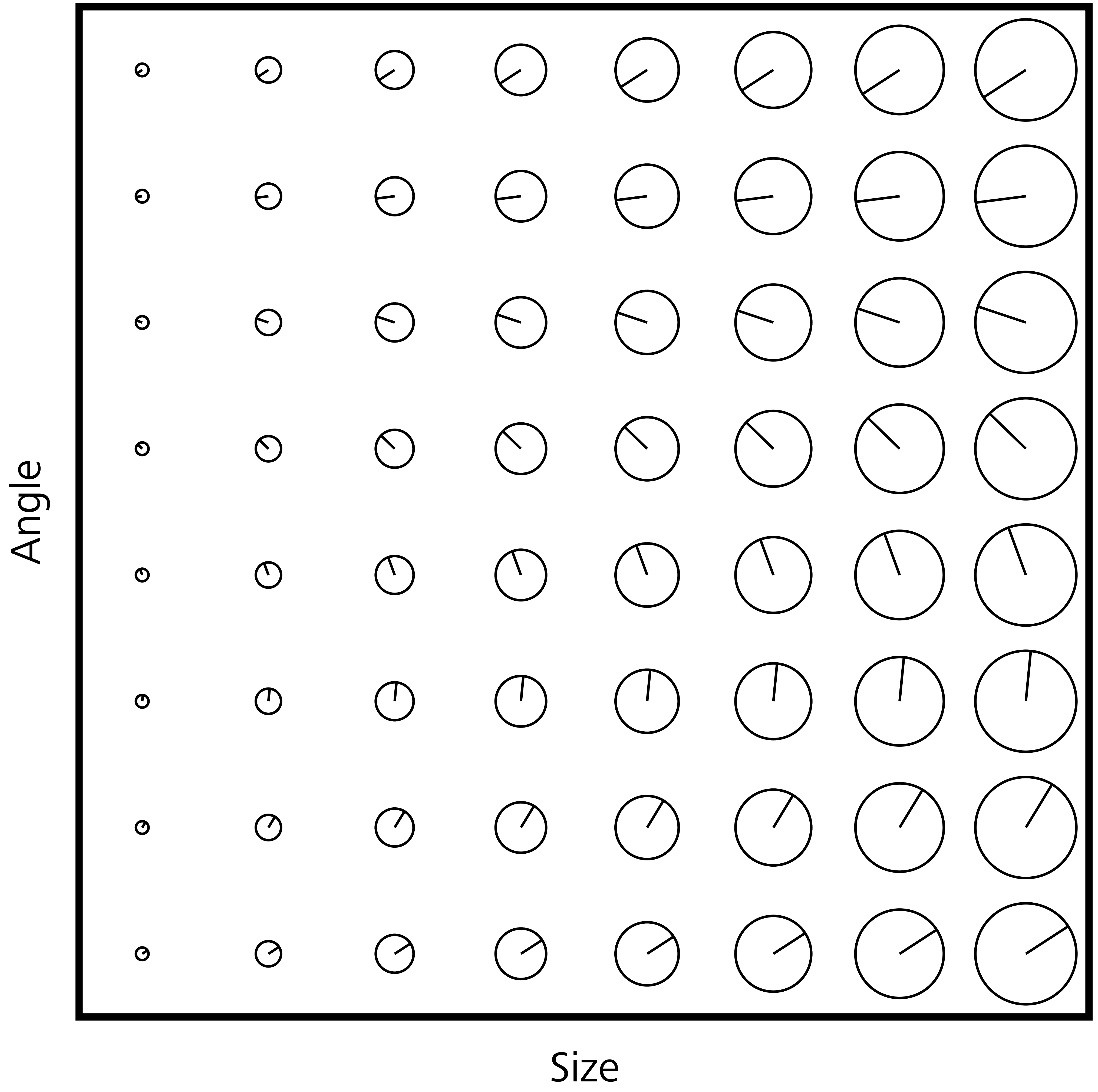
Bayesian iterated learning under an **informativeness prior**



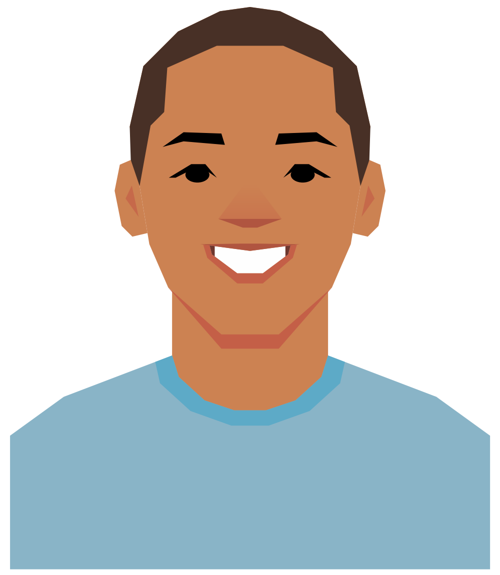
Model results

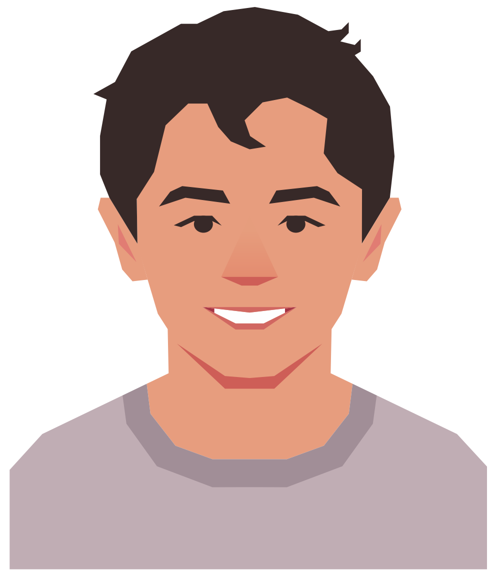


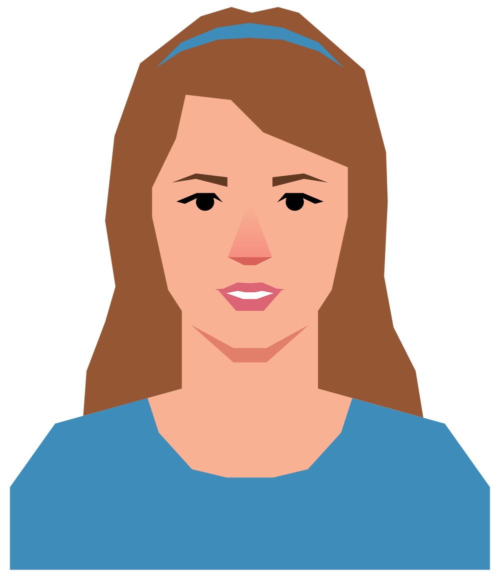
Experimental stimuli



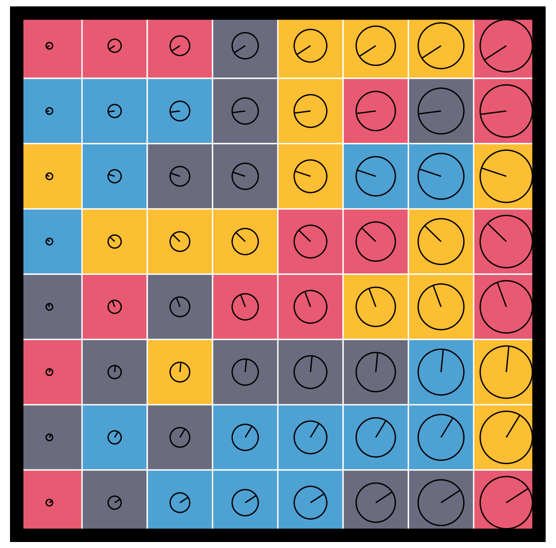
Iterated learning with humans

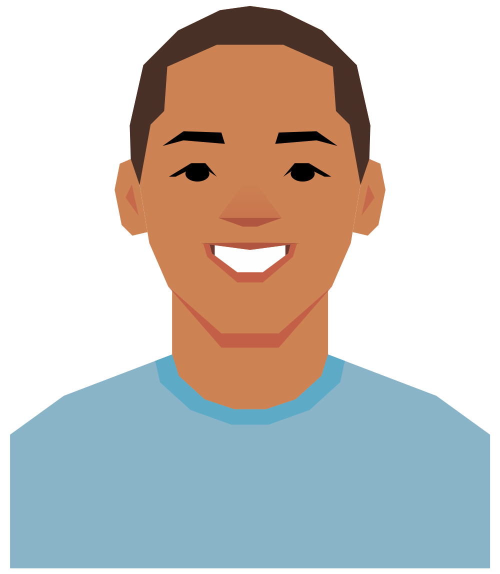


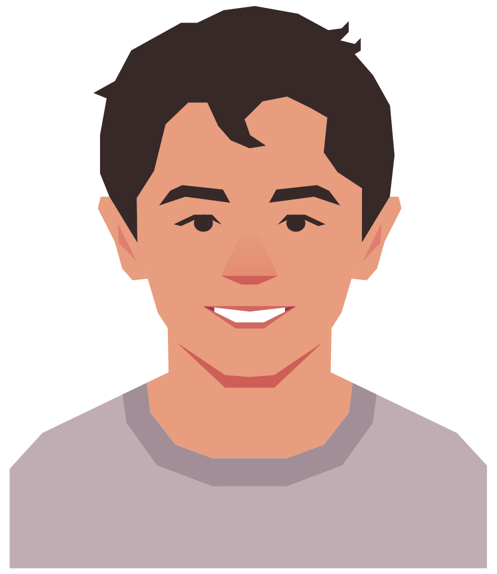




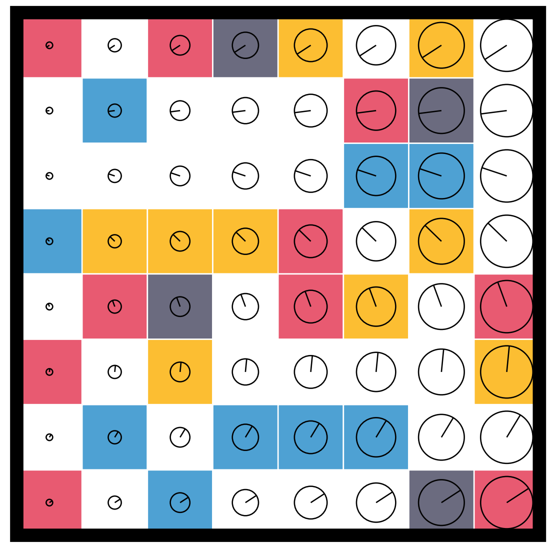
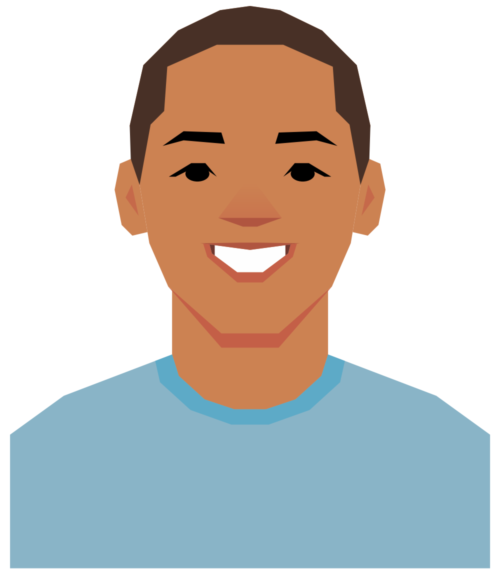
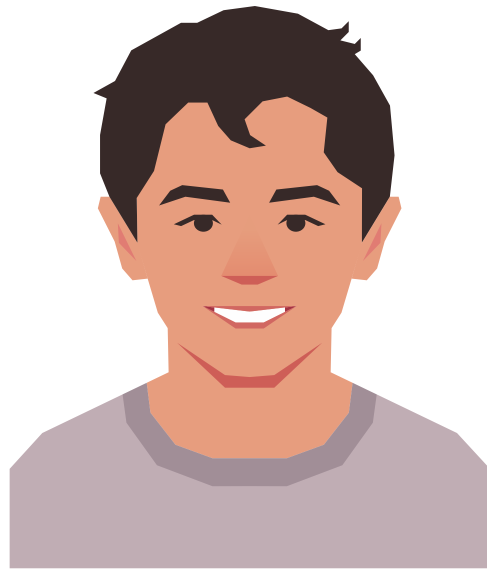
Iterated learning with humans



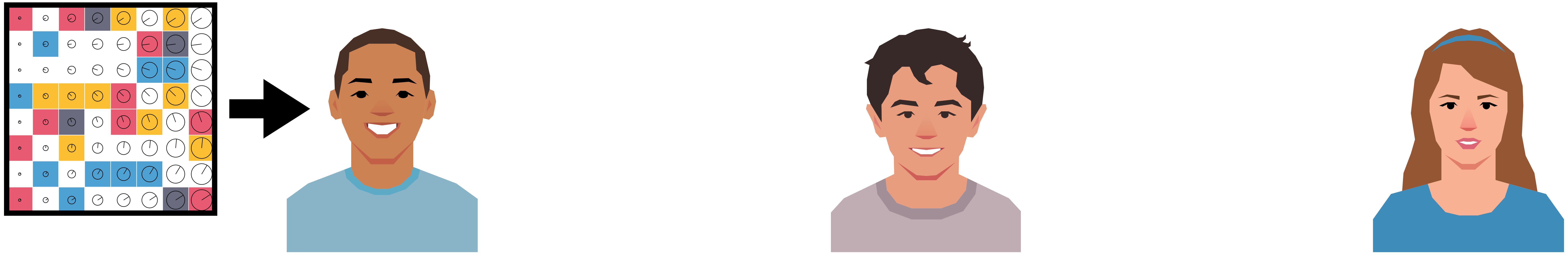




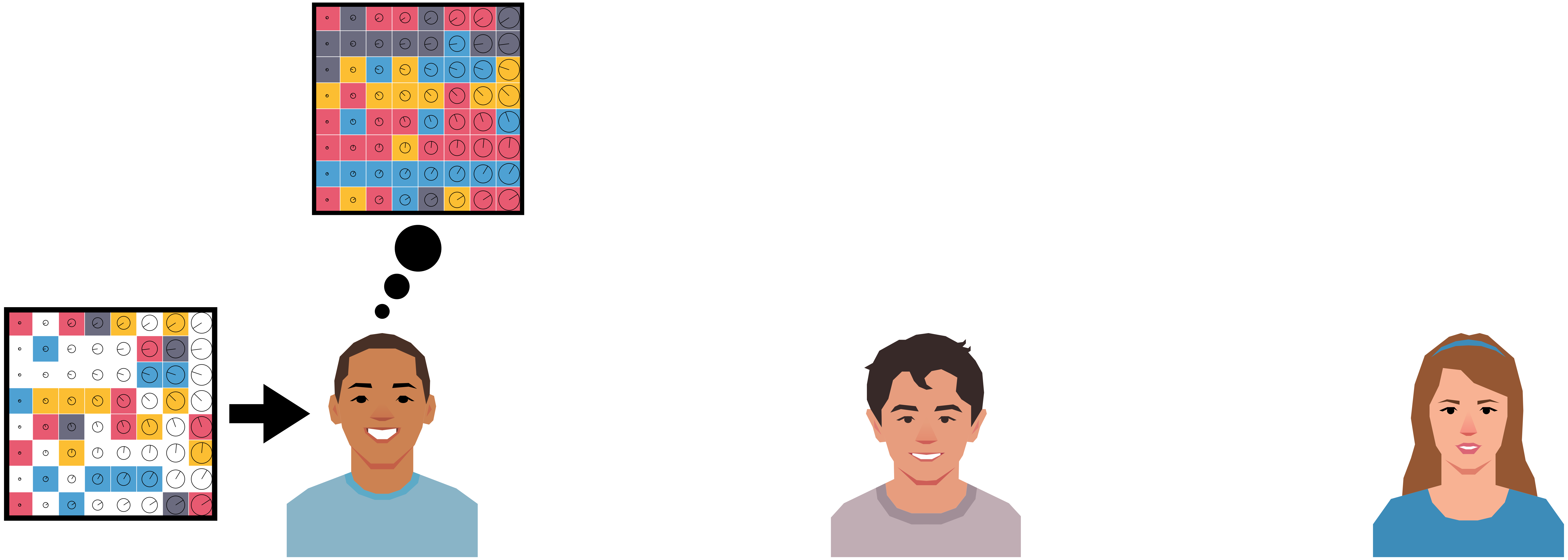
Iterated learning with humans

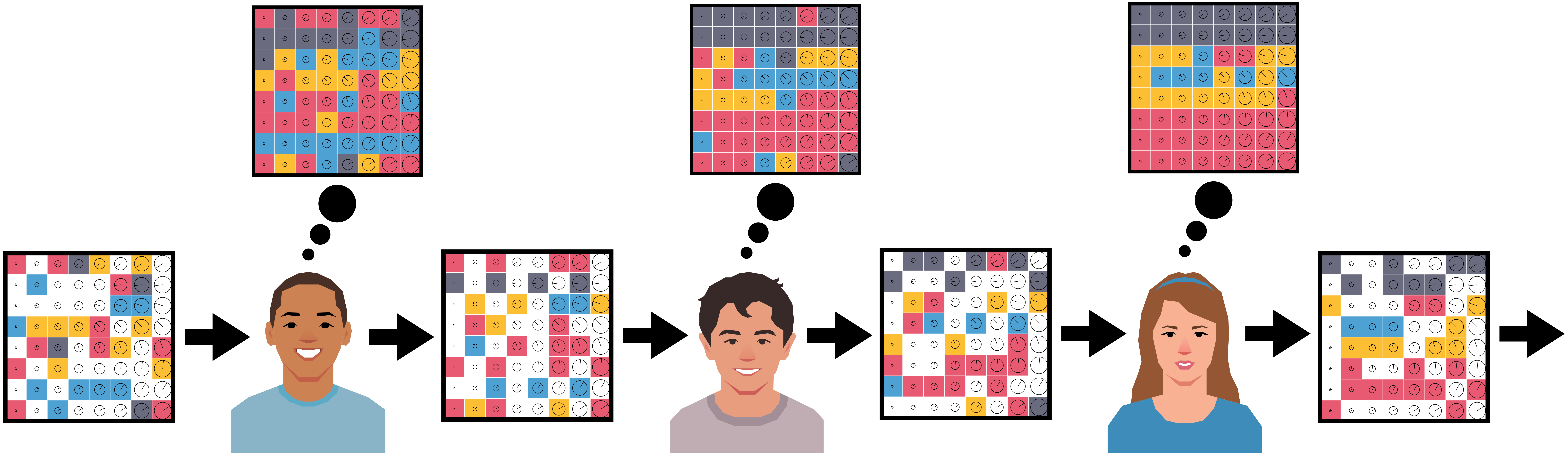

Iterated learning with humans

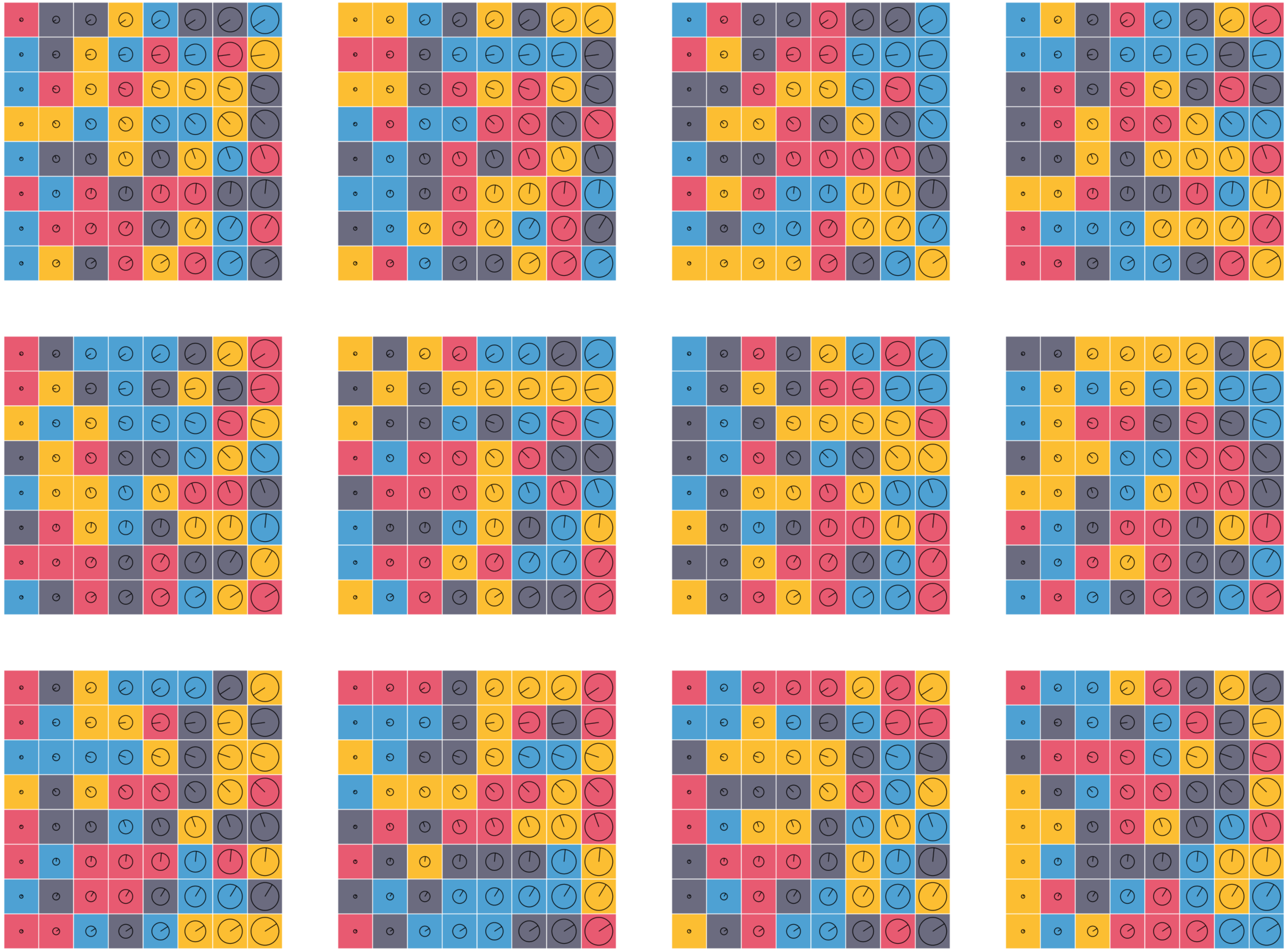


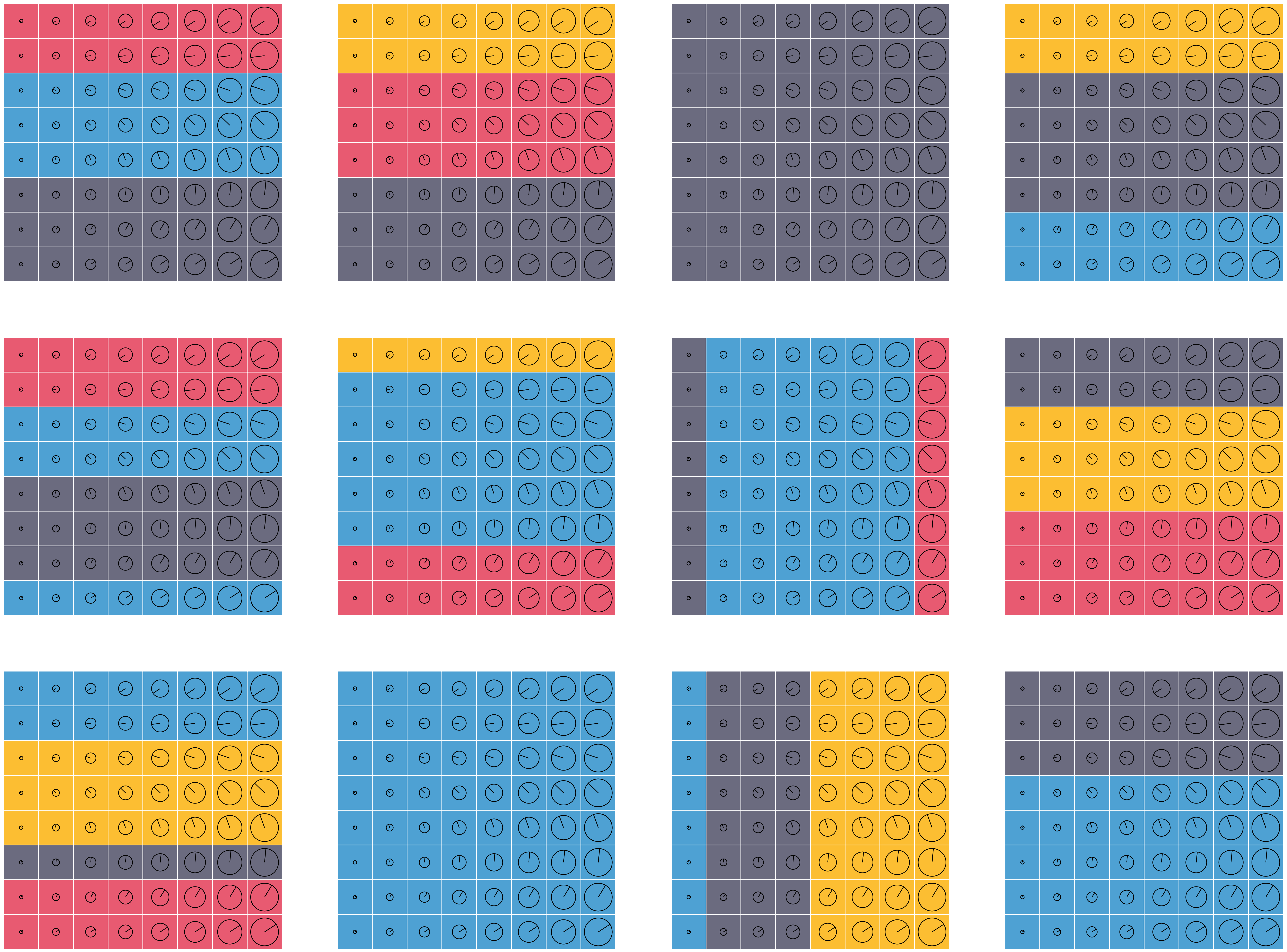
Iterated learning with humans



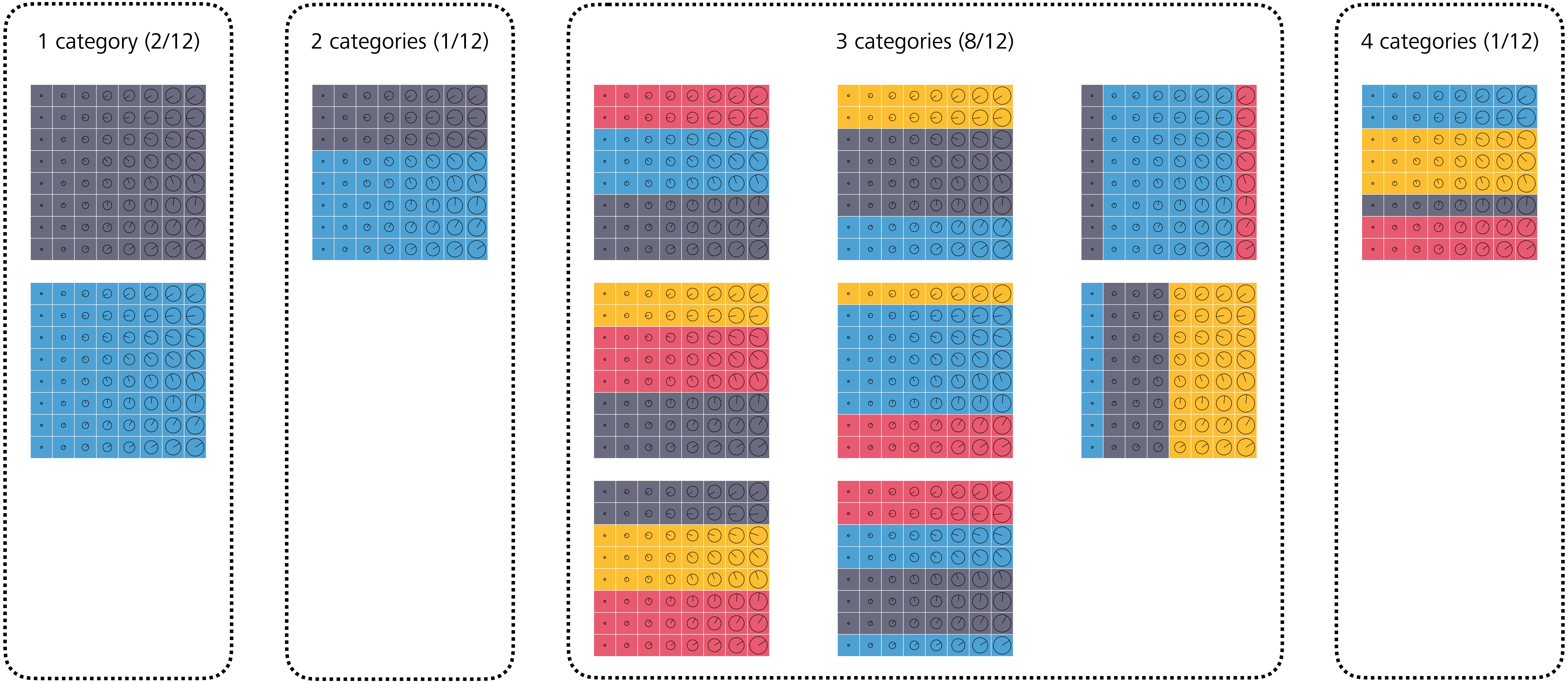
Iterated learning with humans



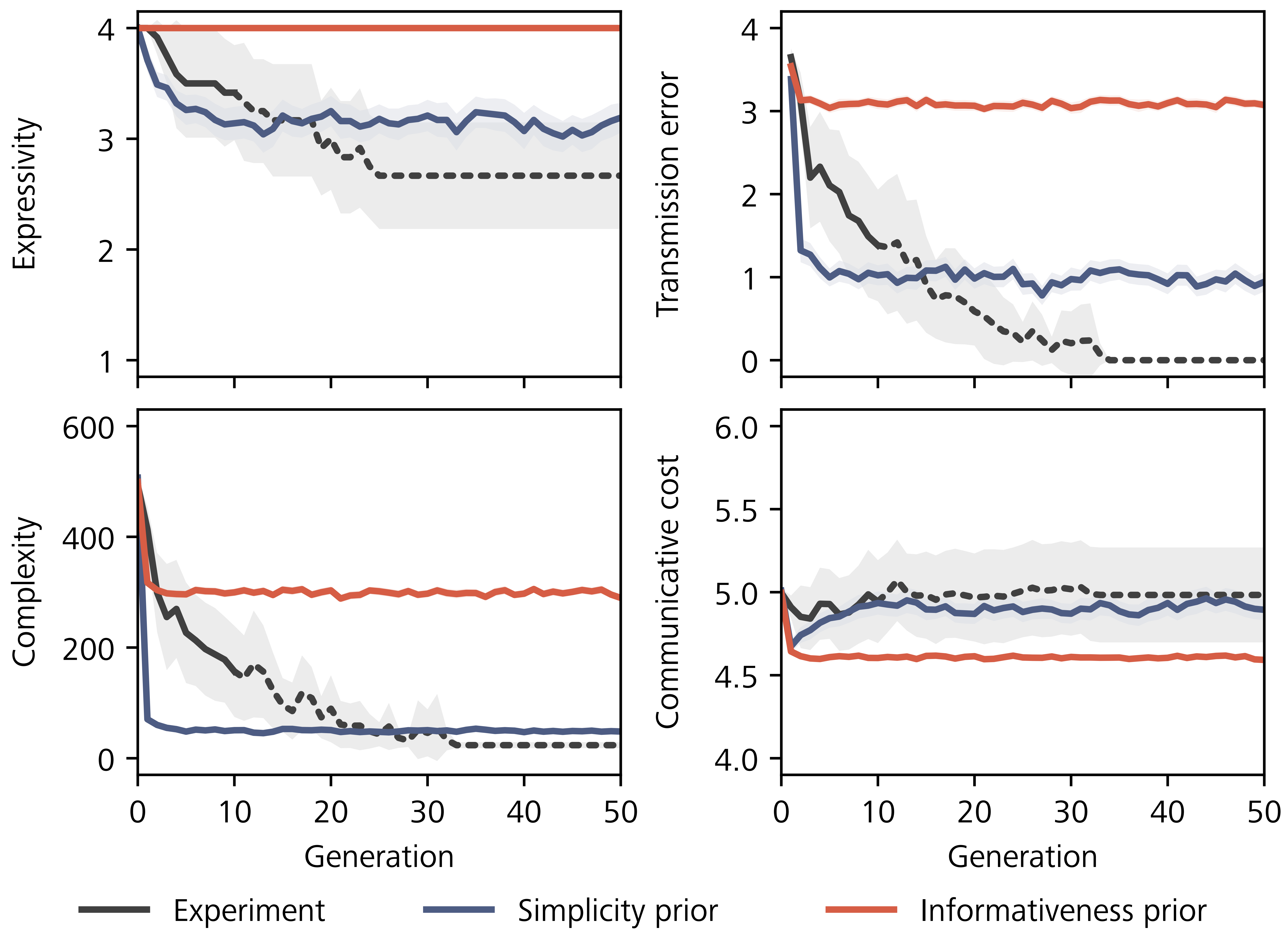




Converged-on category systems

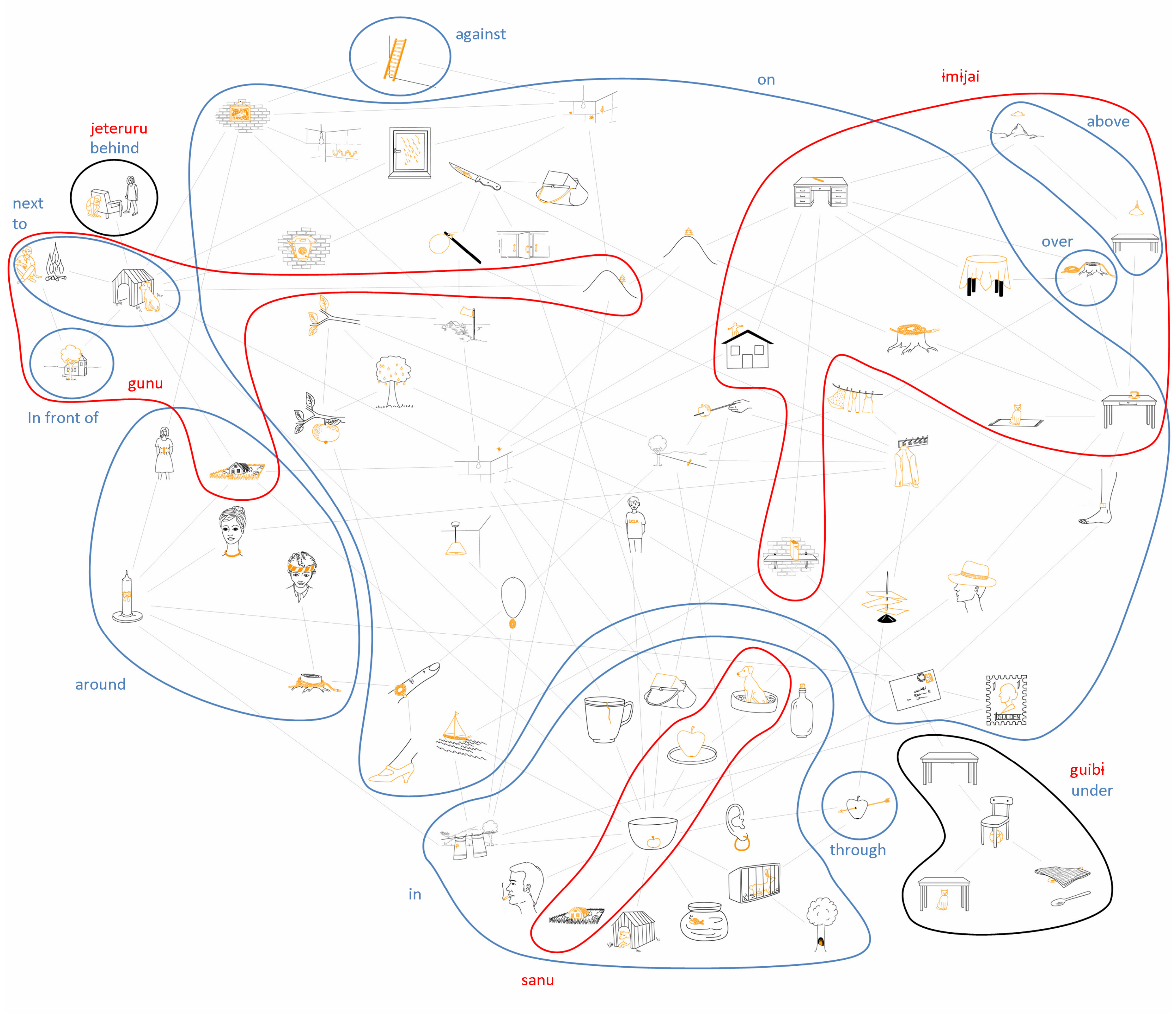


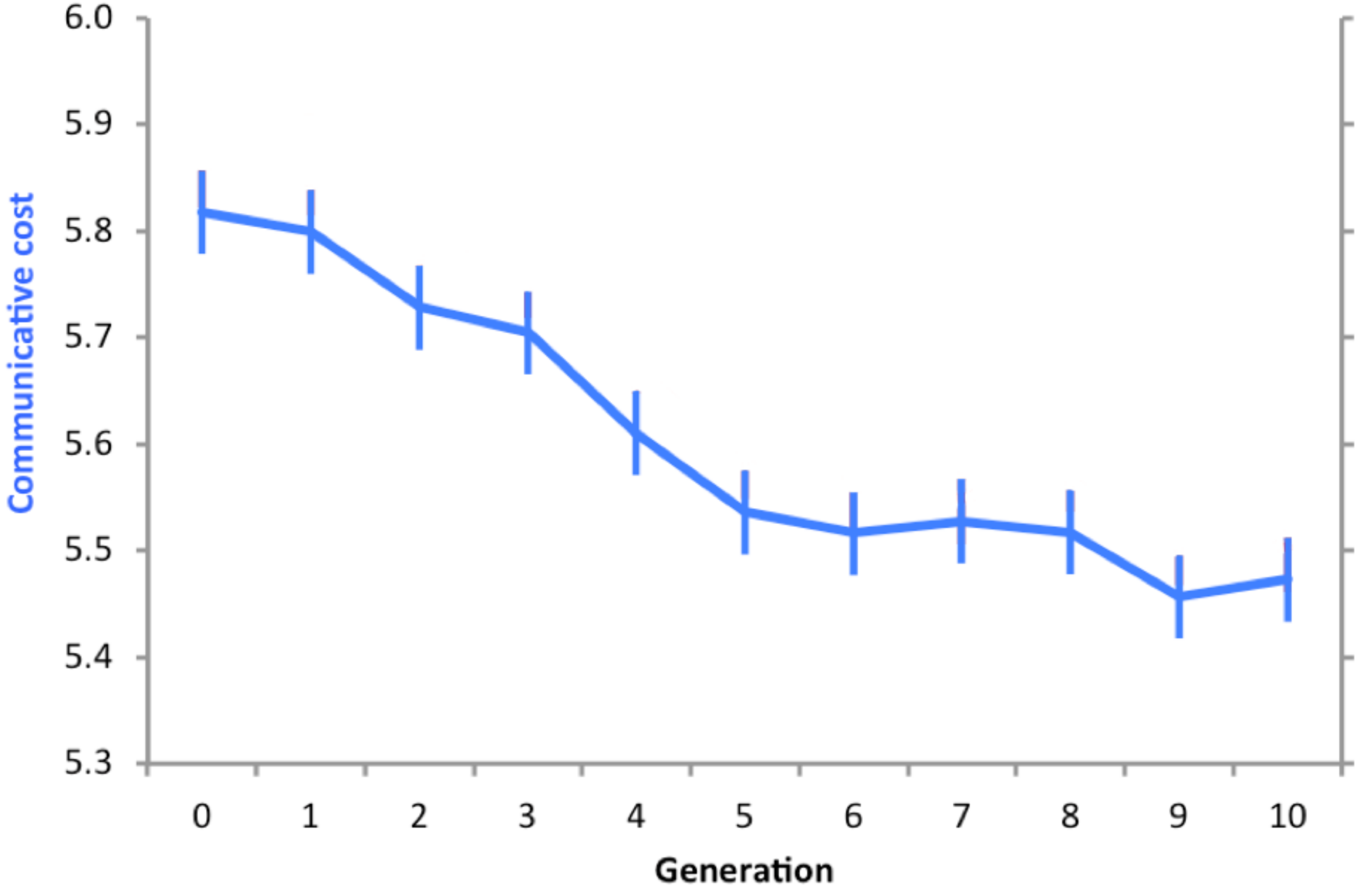
Model results under best-fit parameters



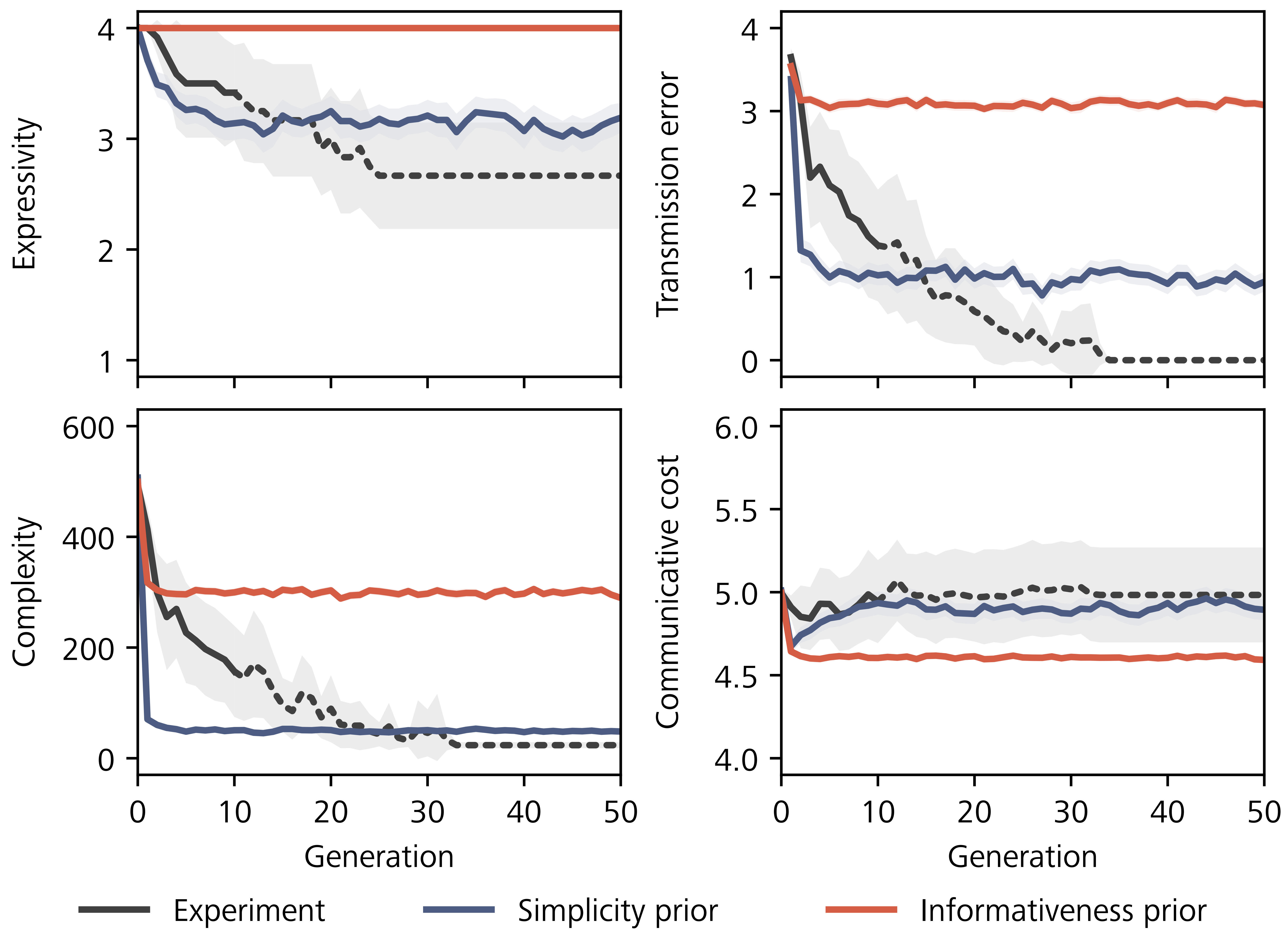
Can iterated learning give rise to informative languages?

Carstensen, Xu, Smith, & Regier (2015)

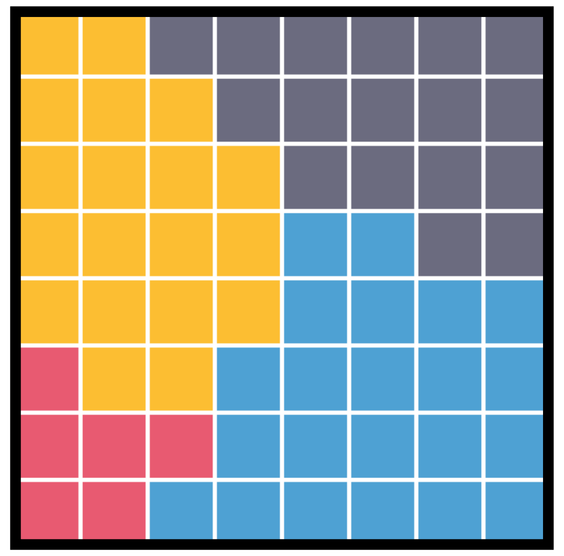




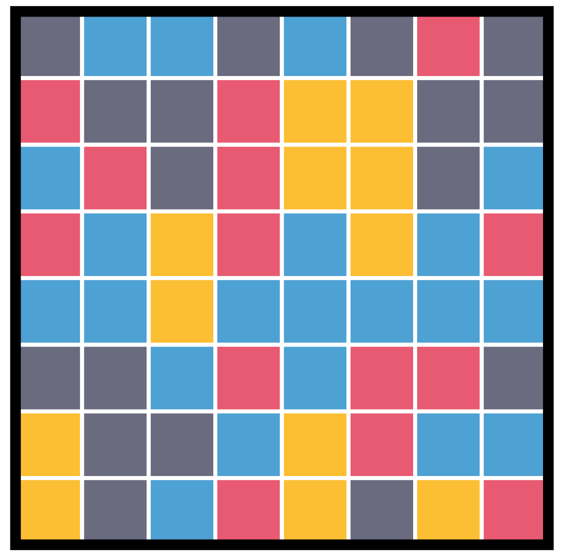
Model results under best-fit parameters



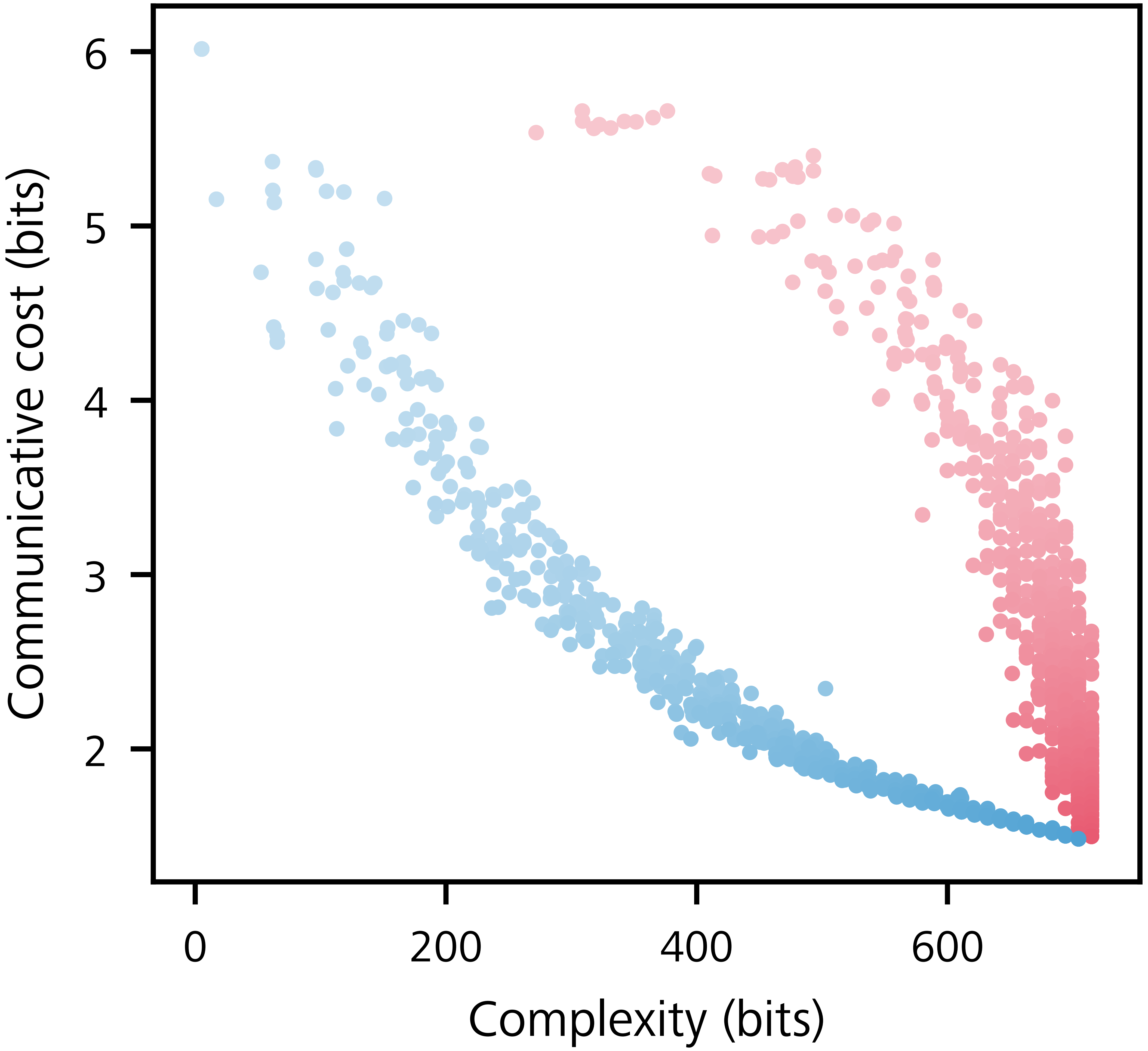
Hallmark features of simple and informative category systems



Compact



Random



Simplicity pressure from induction favours

Few categories

Compactness

Informativeness pressure from interaction favours

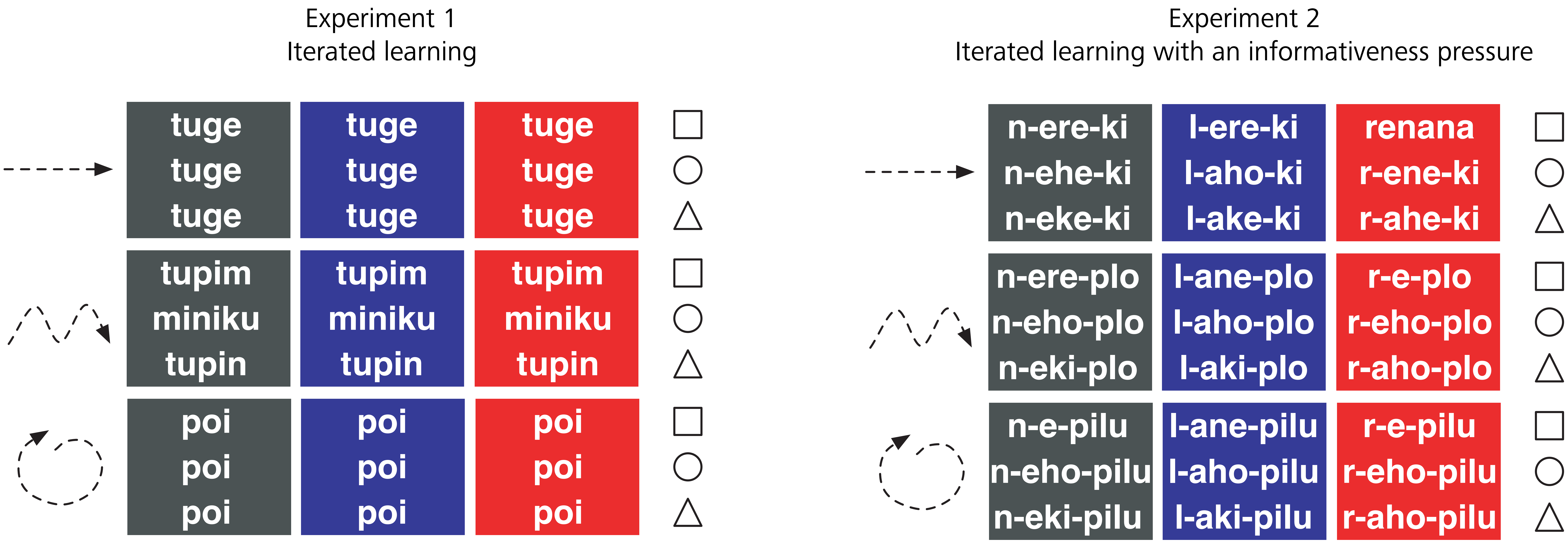
Many categories

Compactness

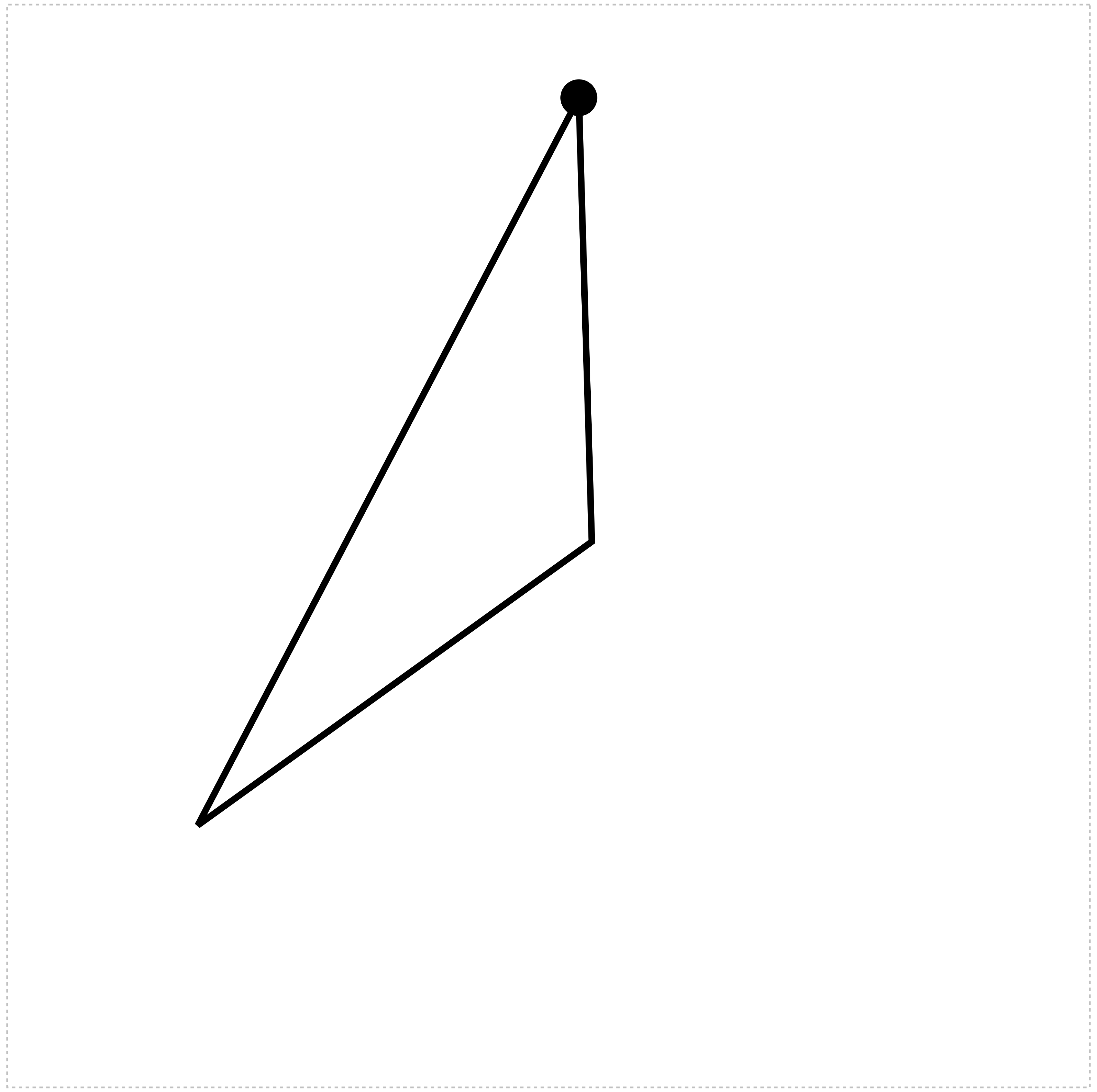
Part 3

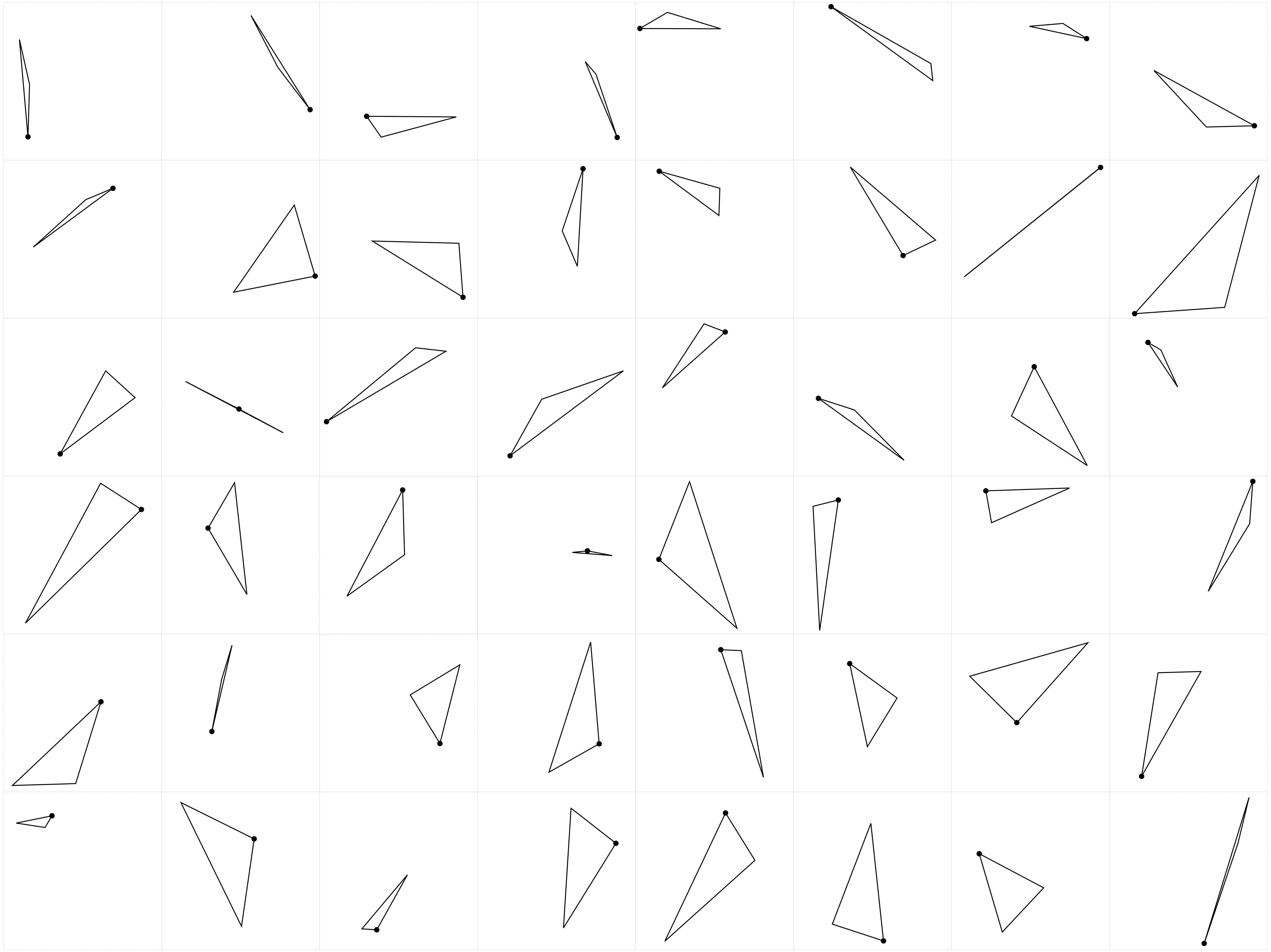
A pressure for informativeness prevents degeneration

Kirby, Cornish, & Smith (2008)



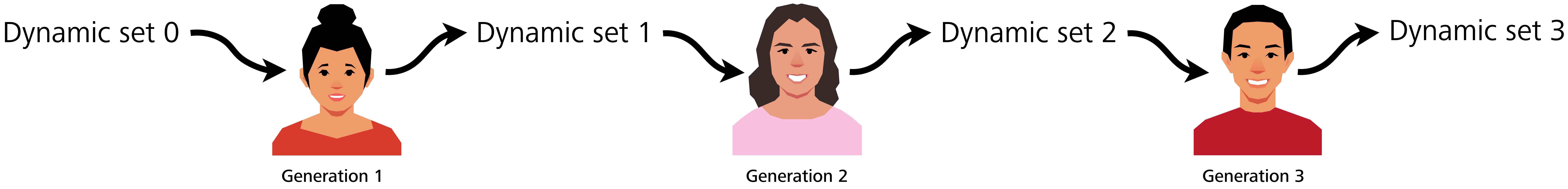
Continuous, open-ended stimulus space



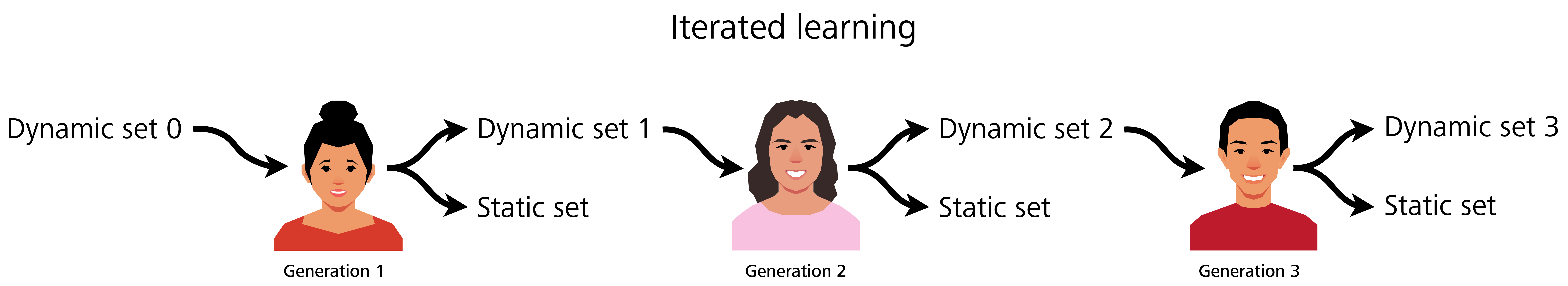


Transmission design

Iterated learning

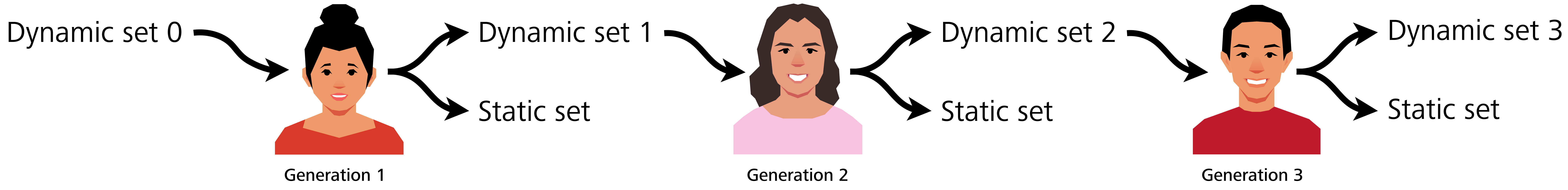


Transmission design

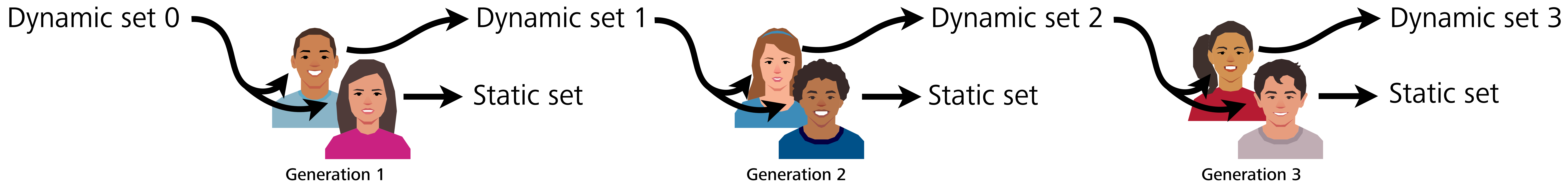


Transmission design

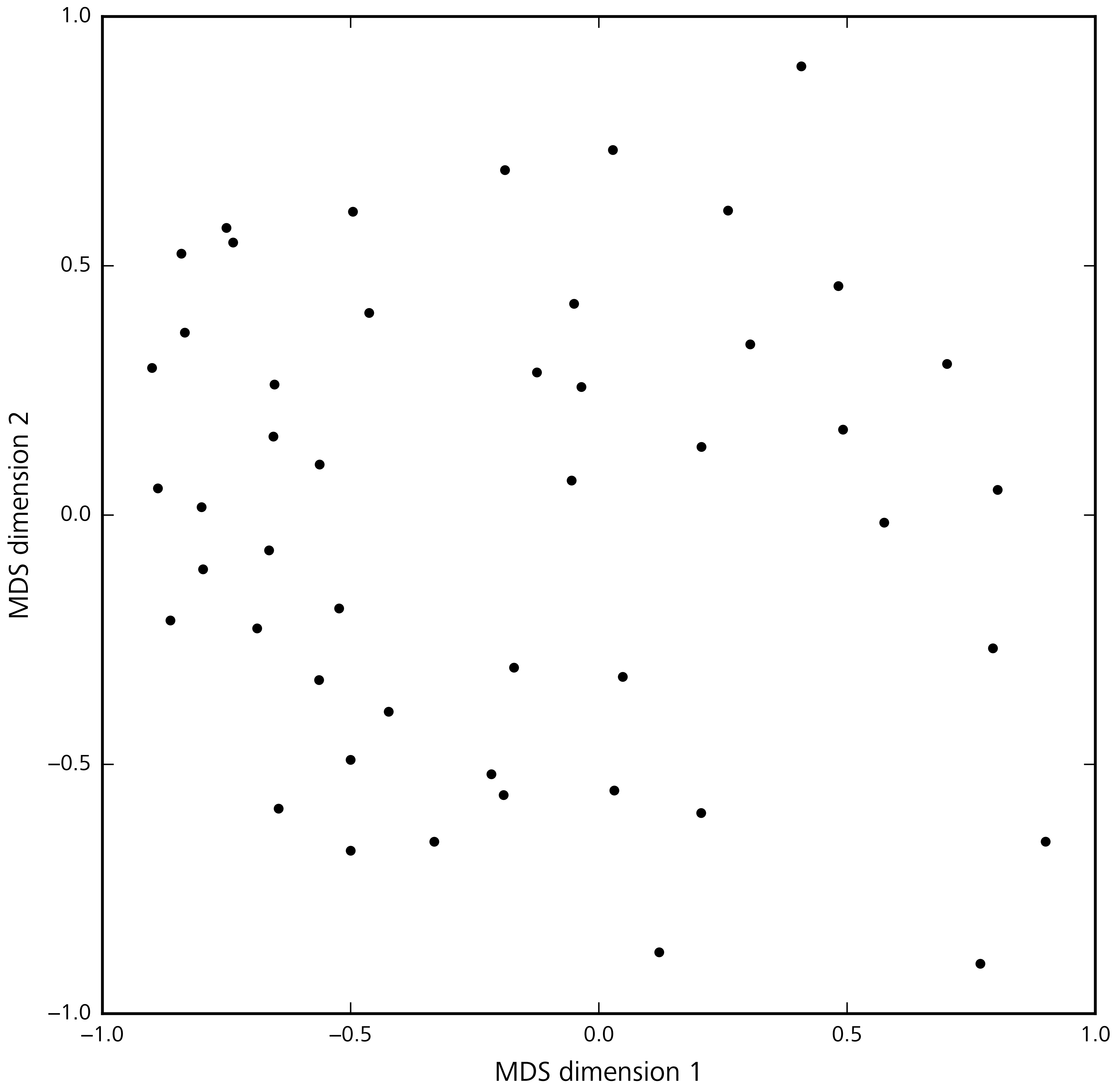
Iterated learning



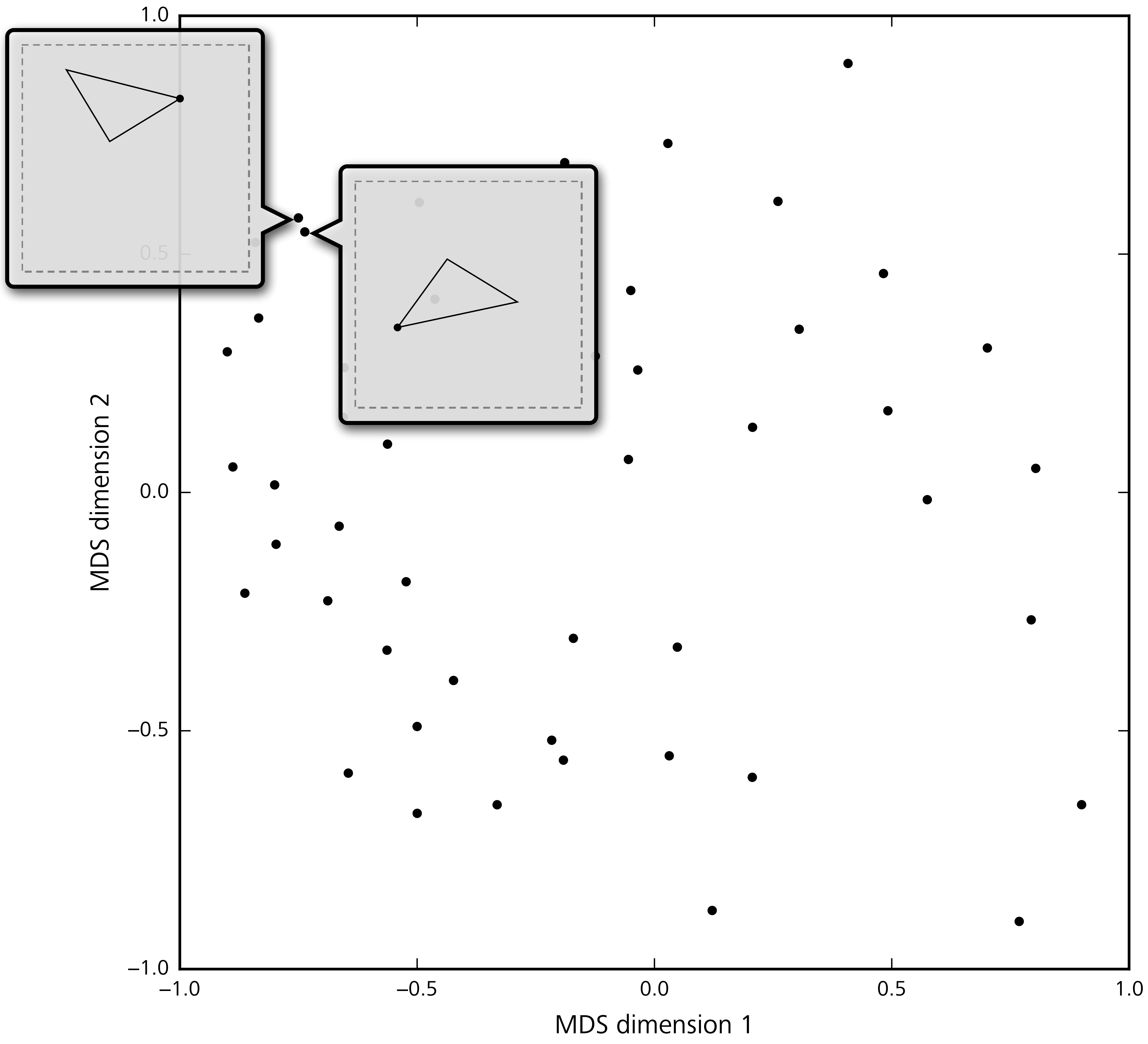
Iterated learning with communicative interaction



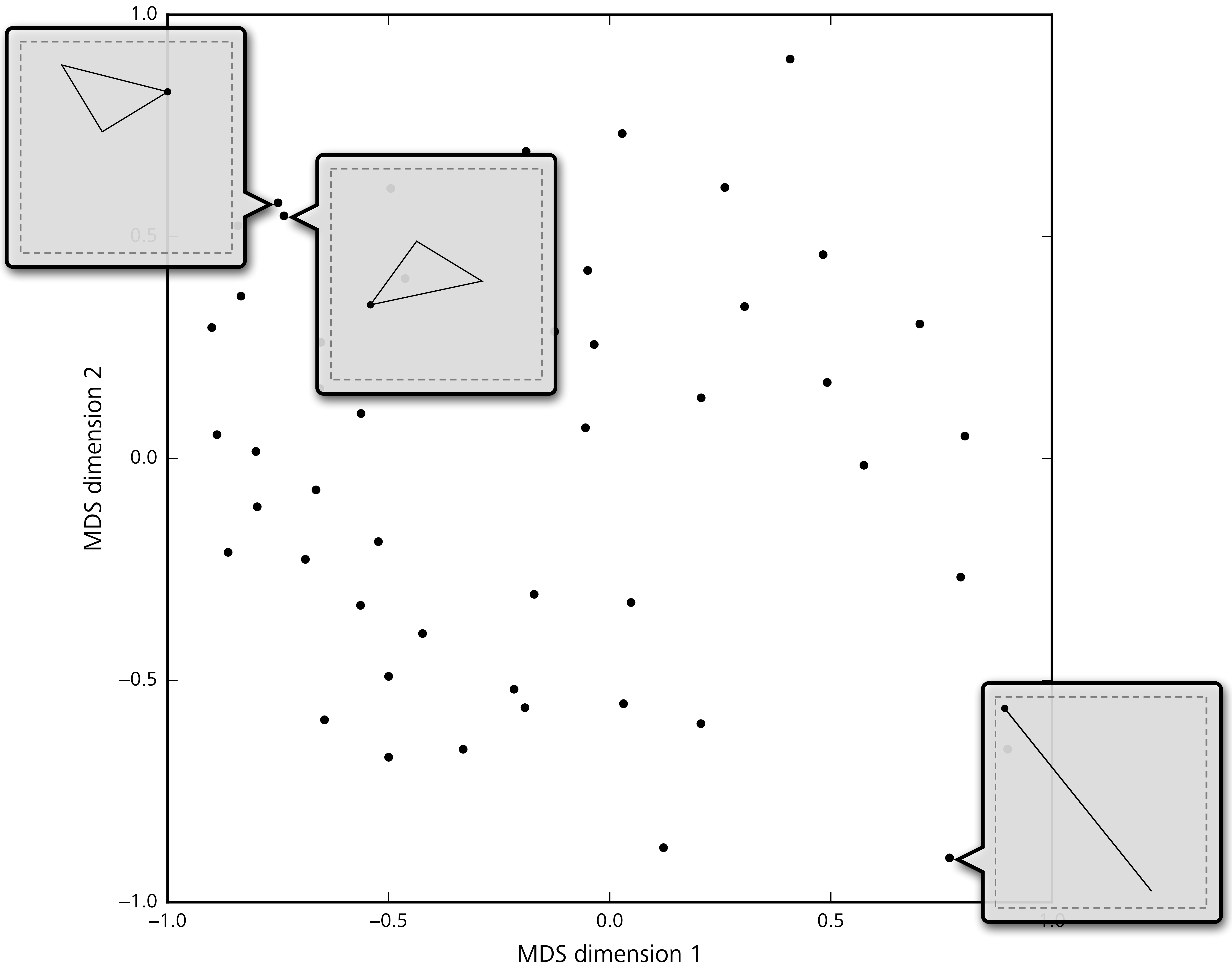
Iterated learning gives rise to discrete categories



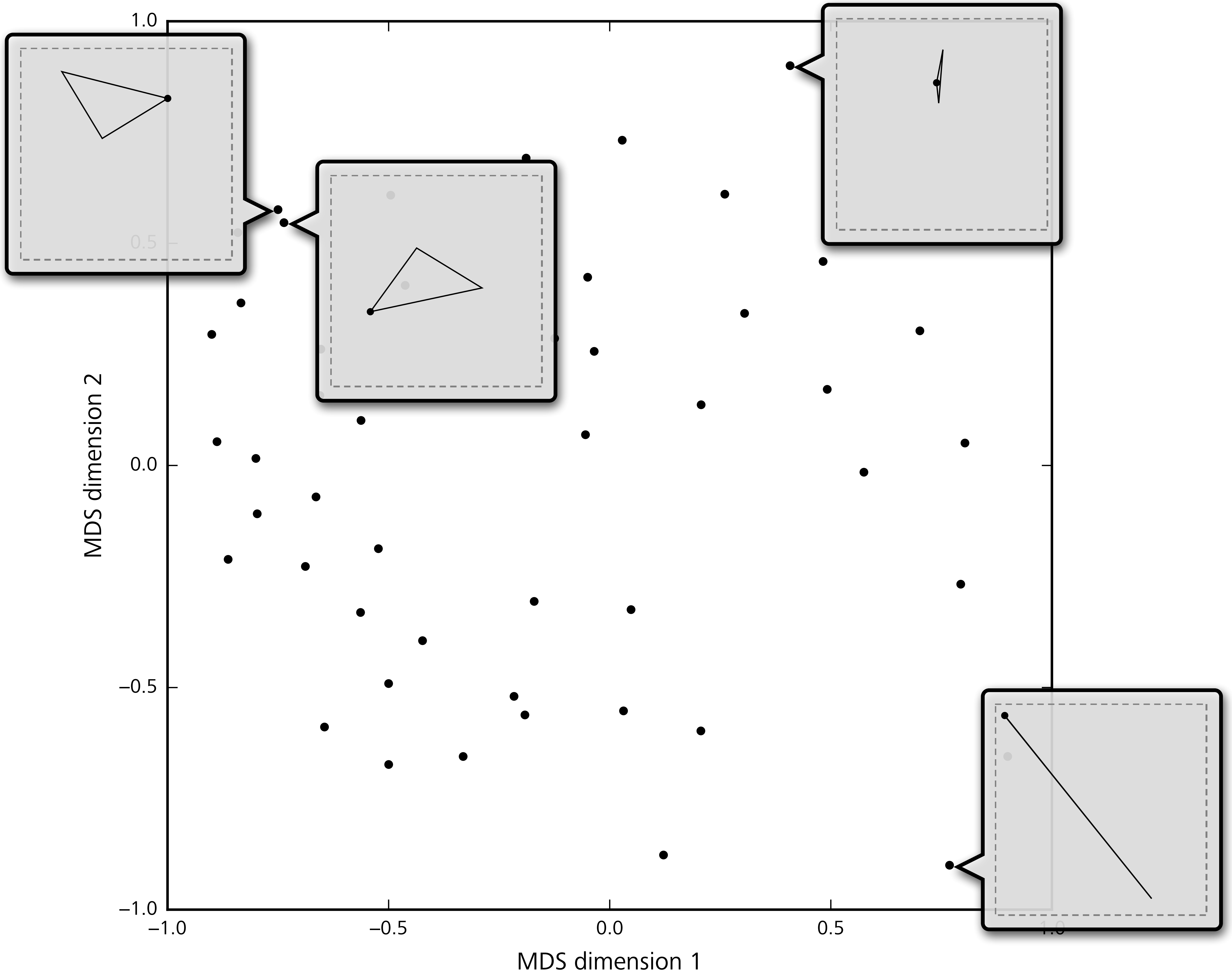
Iterated learning gives rise to discrete categories



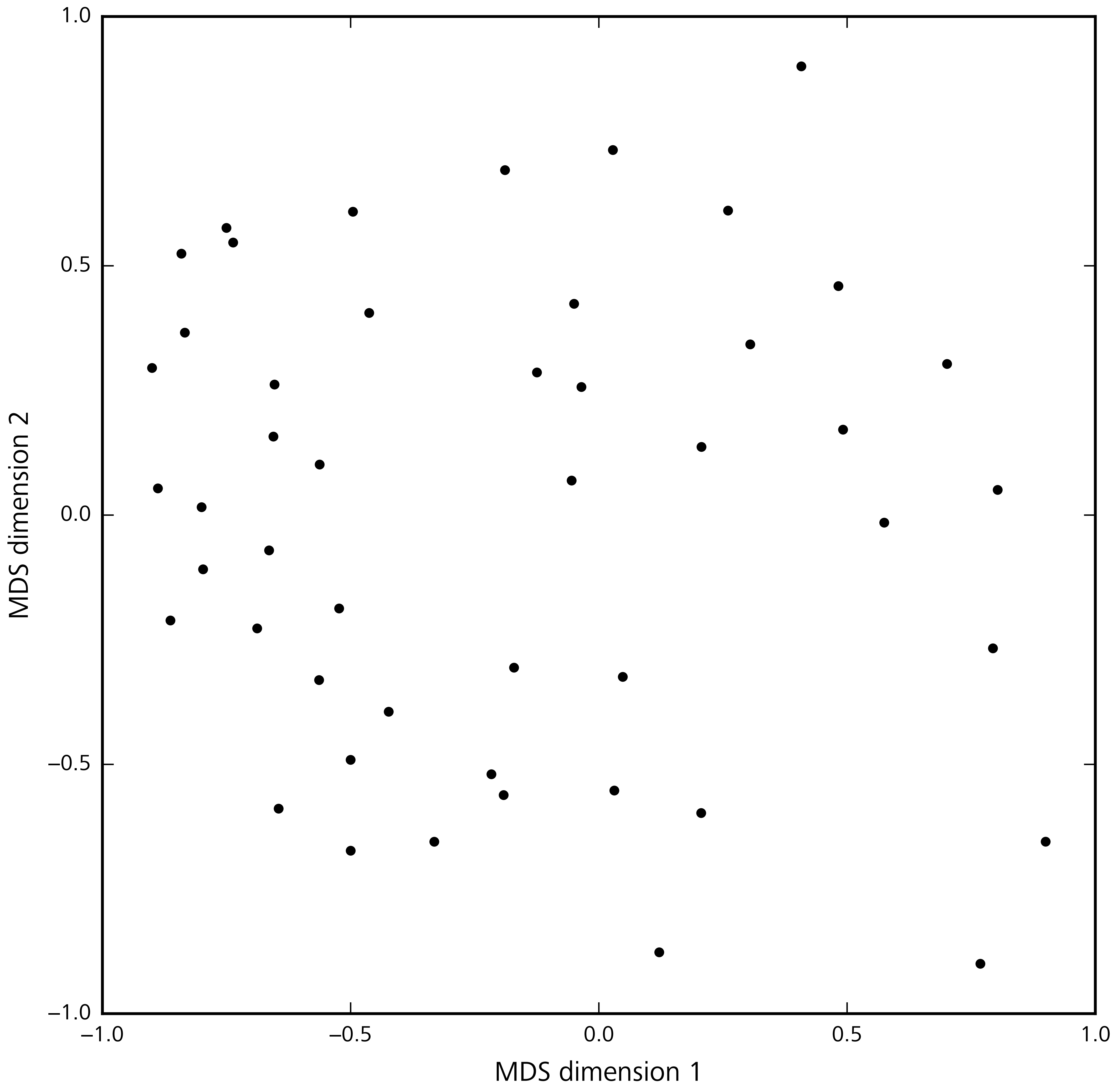
Iterated learning gives rise to discrete categories



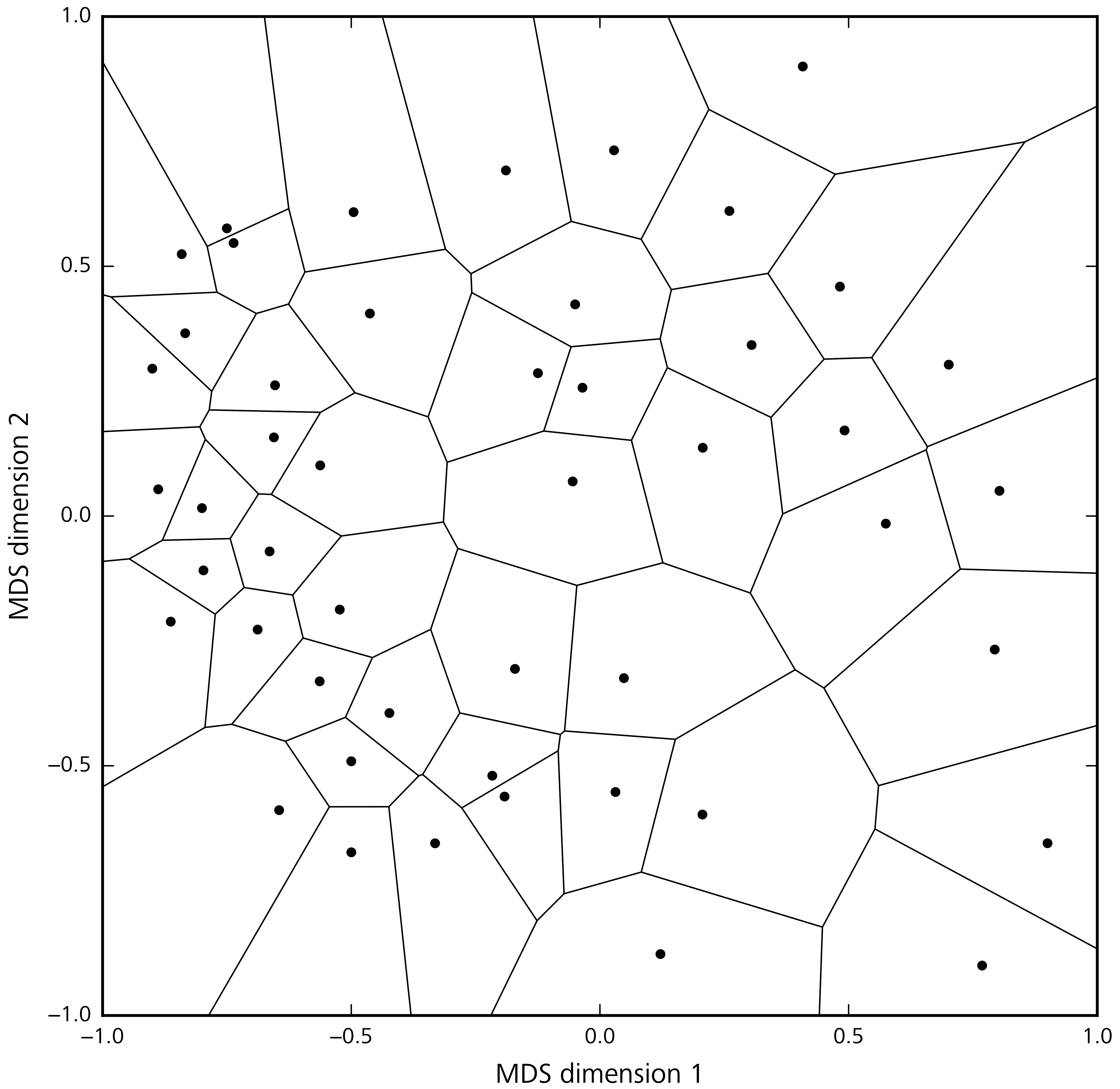
Iterated learning gives rise to discrete categories



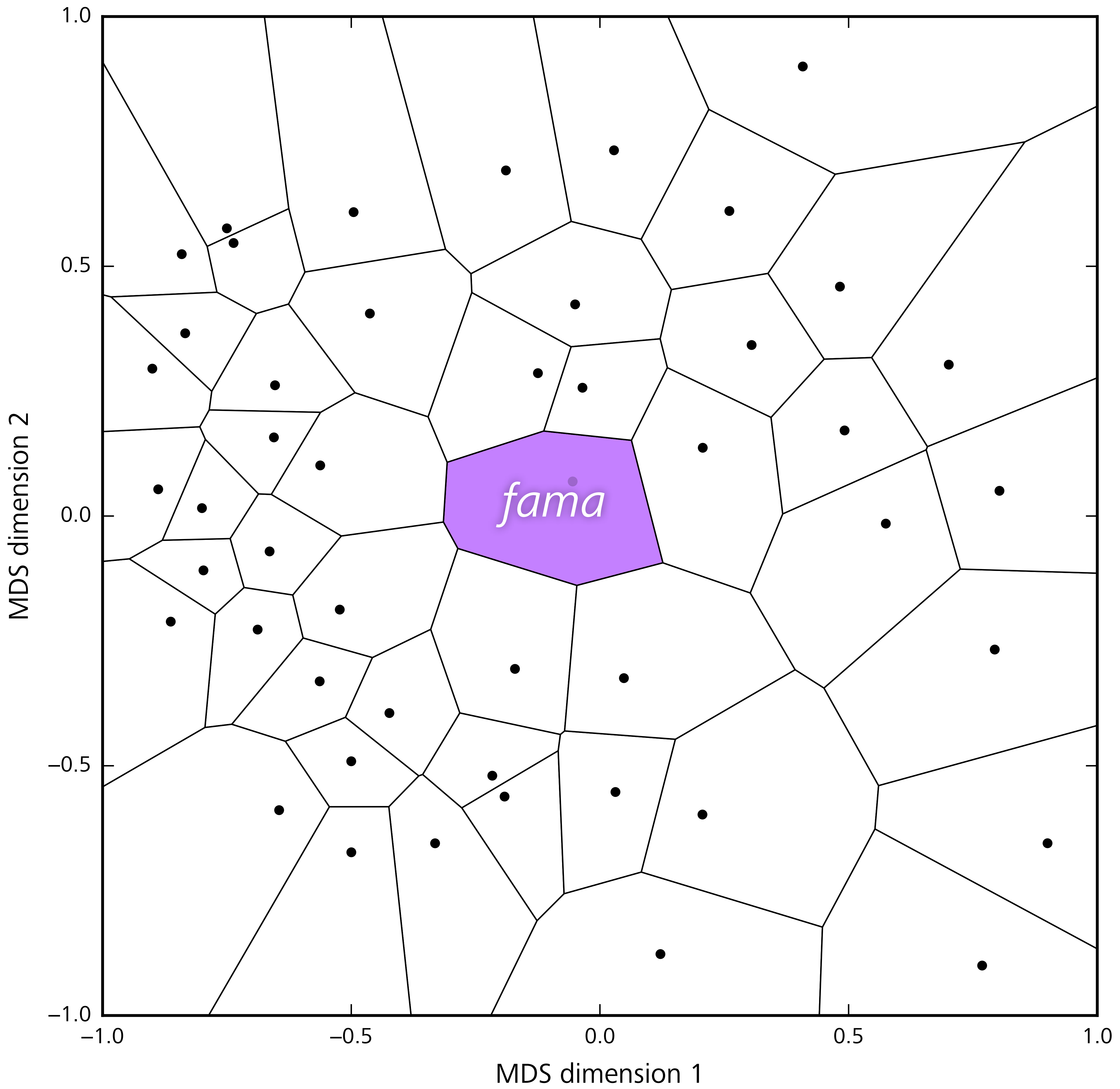
Iterated learning gives rise to discrete categories



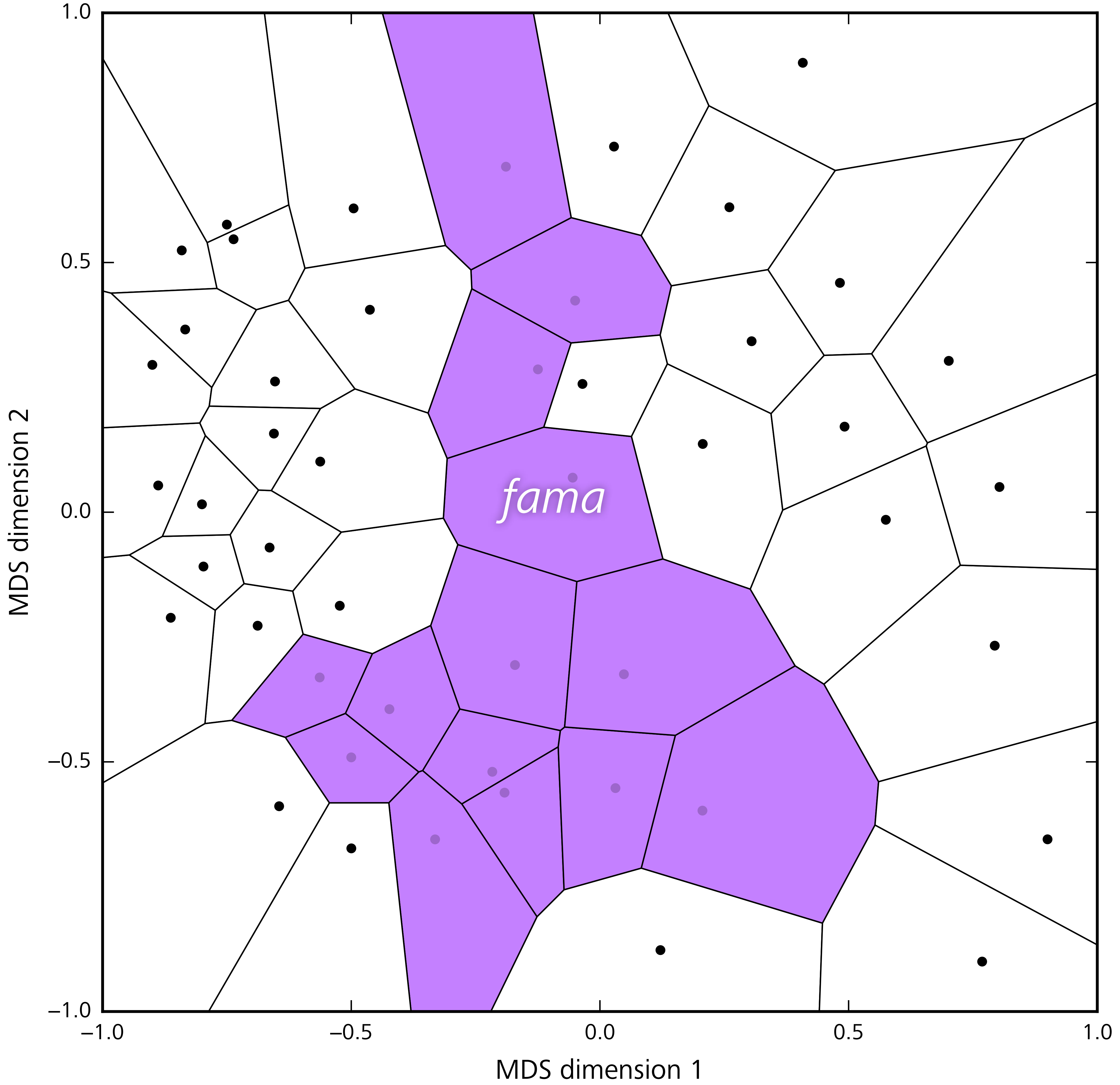
Iterated learning gives rise to discrete categories



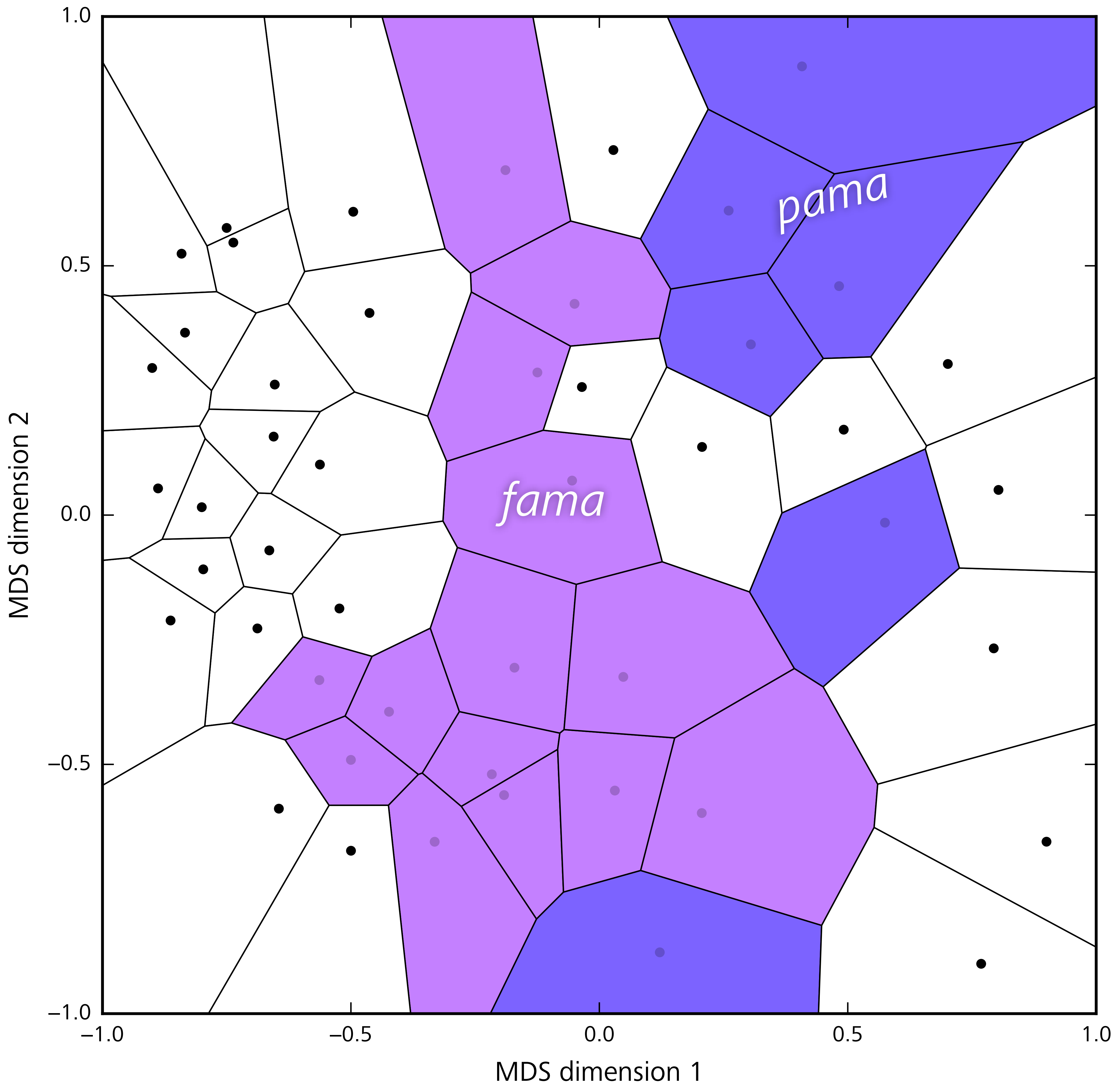
Iterated learning gives rise to discrete categories



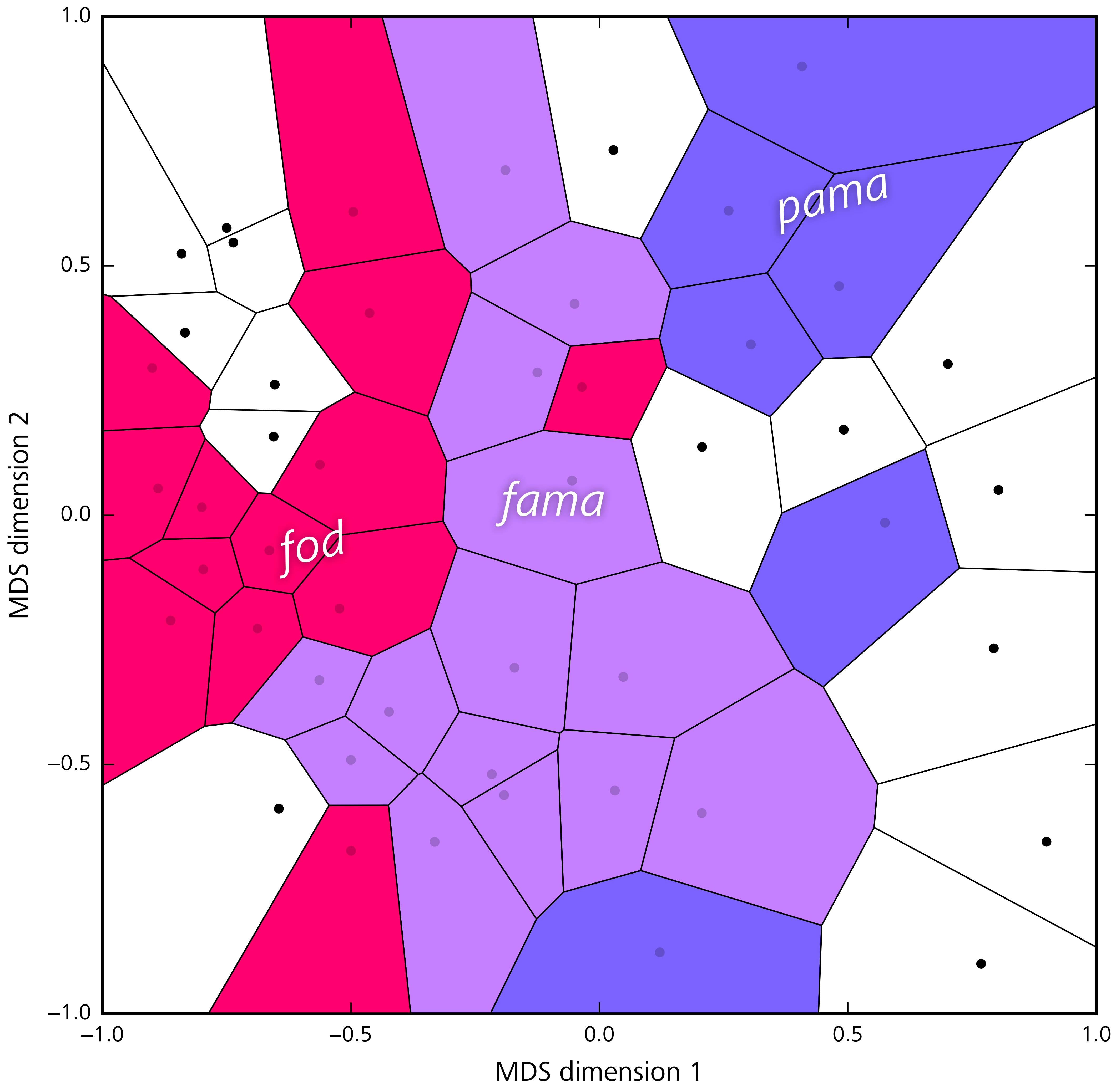
Iterated learning gives rise to discrete categories



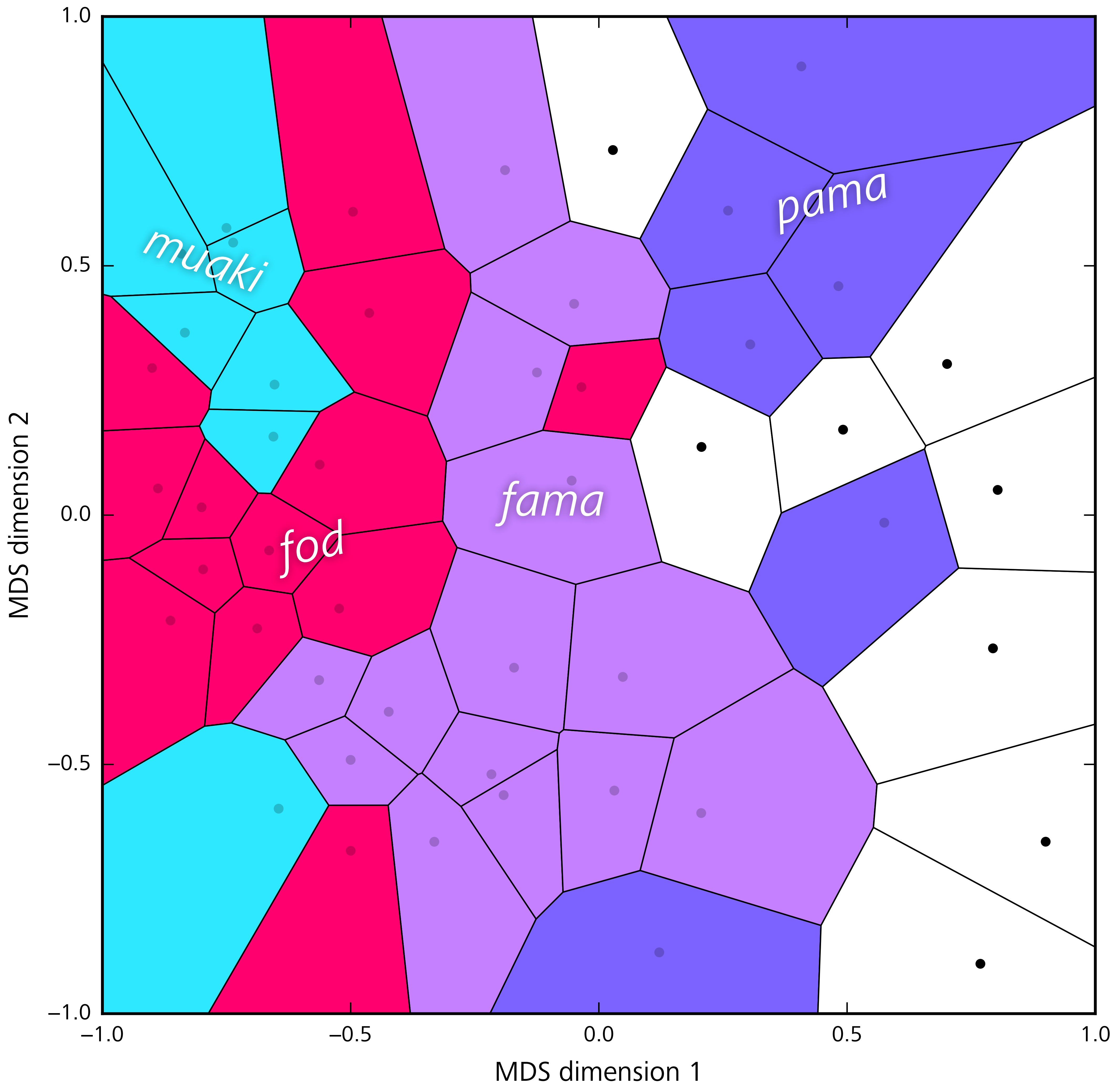
Iterated learning gives rise to discrete categories



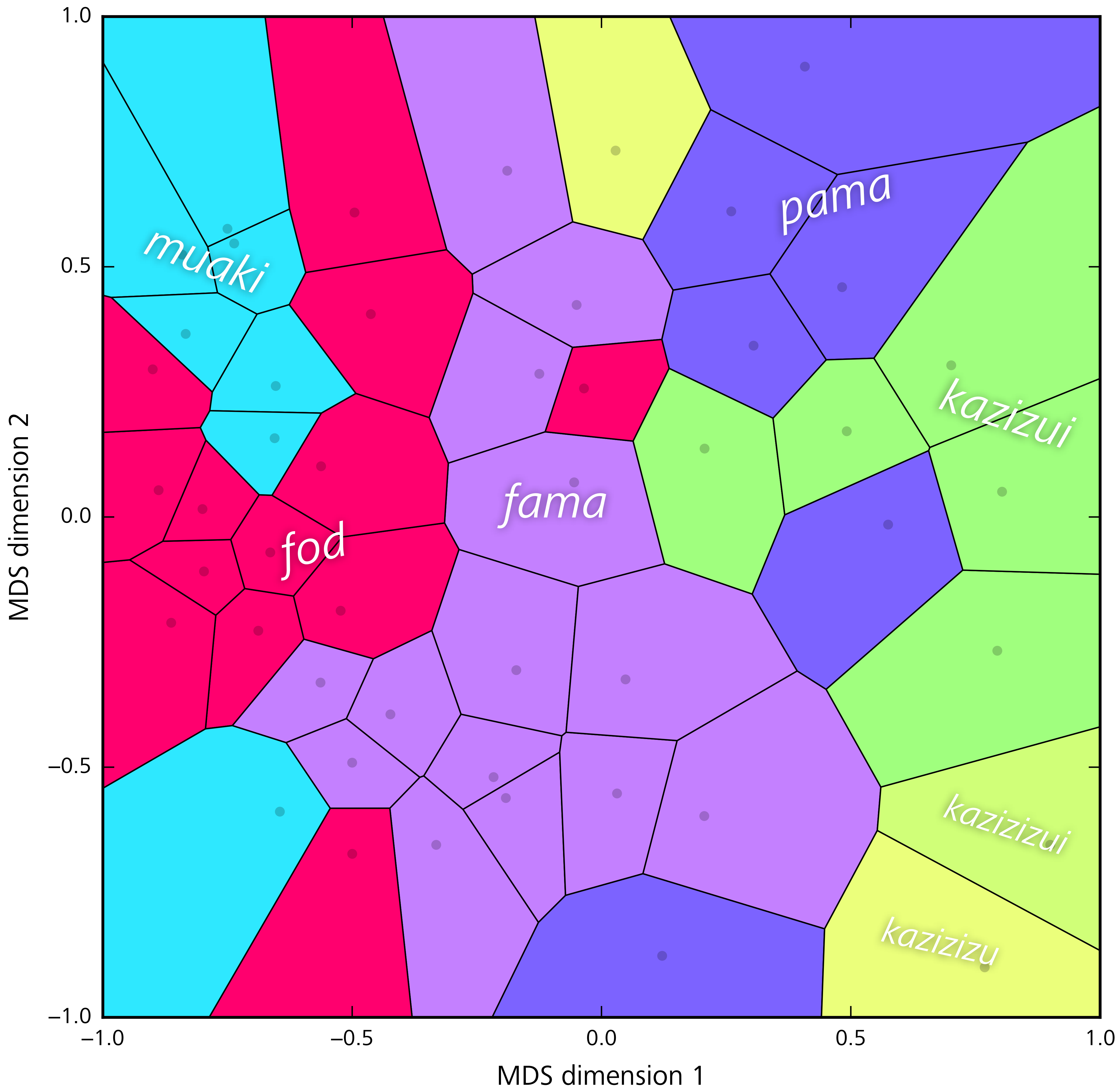
Iterated learning gives rise to discrete categories



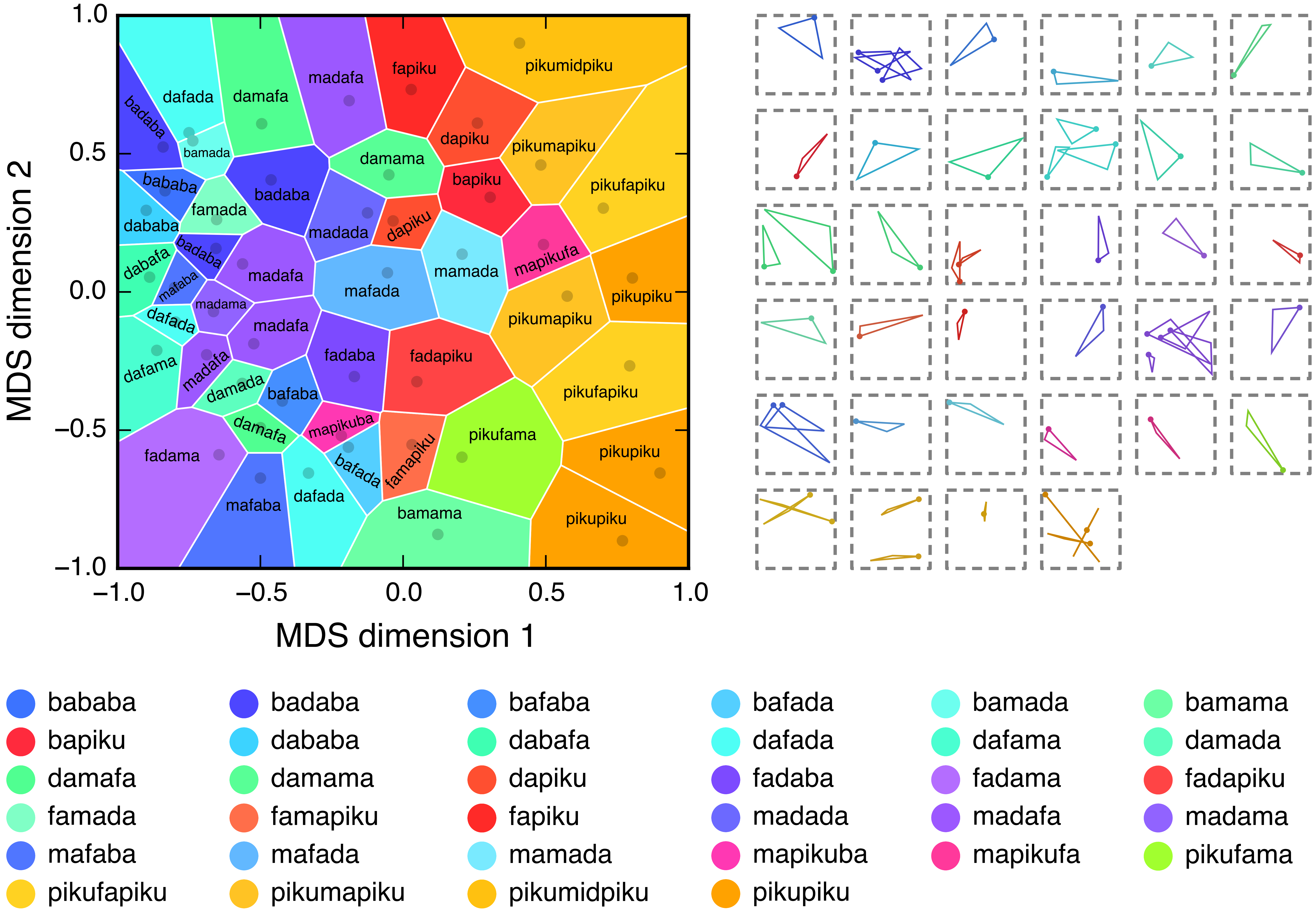
Iterated learning gives rise to discrete categories



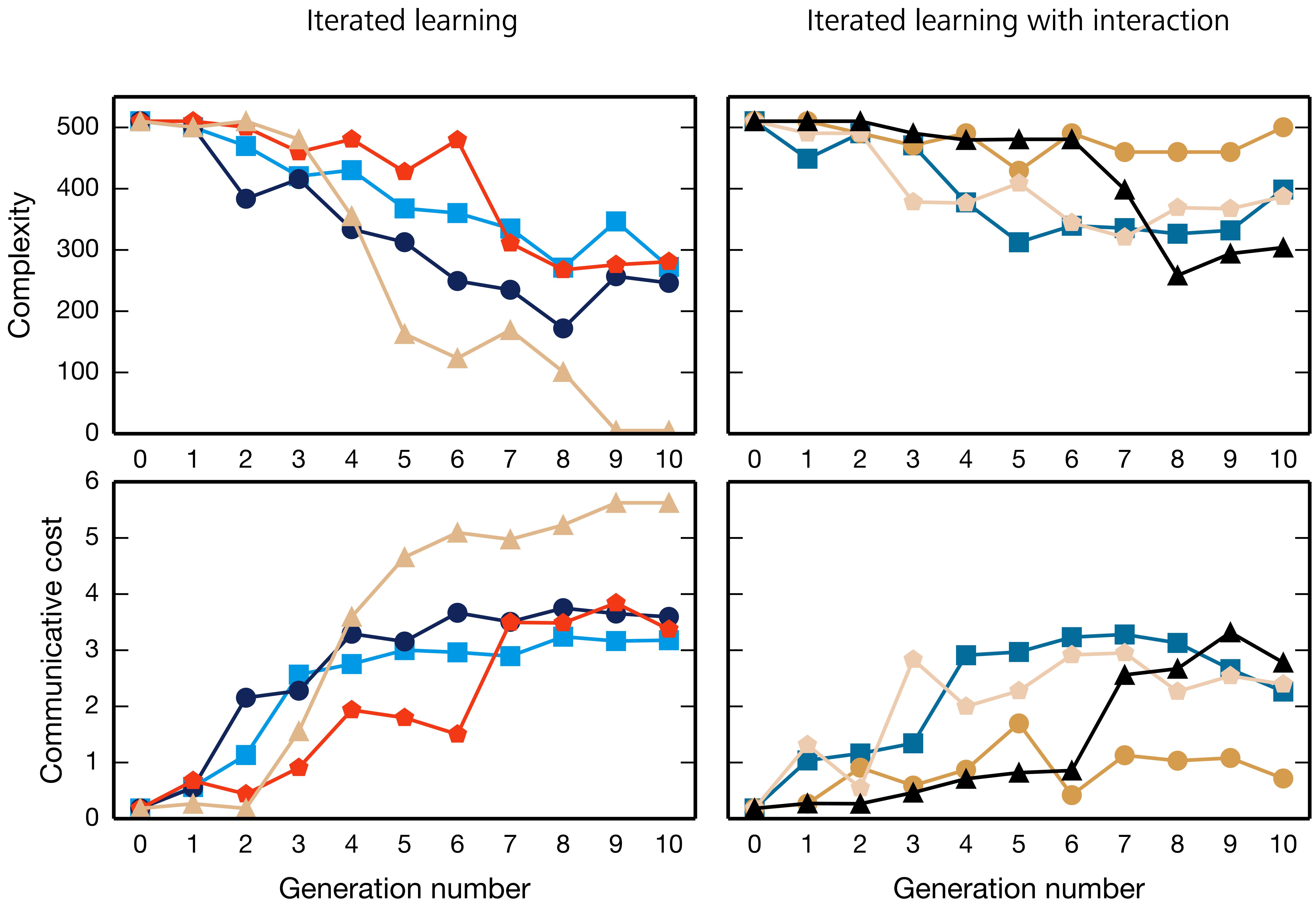
Iterated learning gives rise to discrete categories



Communicative interaction gives rise to sublexical structure



Communicative interaction gives rise to sublexical structure



Conclusions

Conclusions

- Languages are shaped by competing pressures from induction and interaction
- The human inductive bias is best characterized by a preference for simplicity
- Therefore, iterated learning gives rise to simple, inexpressive category systems with simple, compact structure
  Side-note: Compact structure also happens to be a feature of informativeness, obscuring the mechanism
- But! The presence of communicative interaction prevents this process getting out of hand by permitting the emergence of higher-level forms of linguistic structure
- The framework developed in the CLE (which, by the way, has many parallels with a body of work from Regier and colleagues) is resilient to more realistic assumptions about meaning

Thanks!