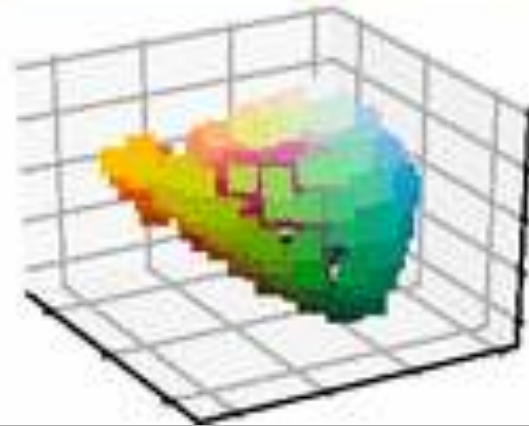# Reinforcement Learning: Principles and Applications
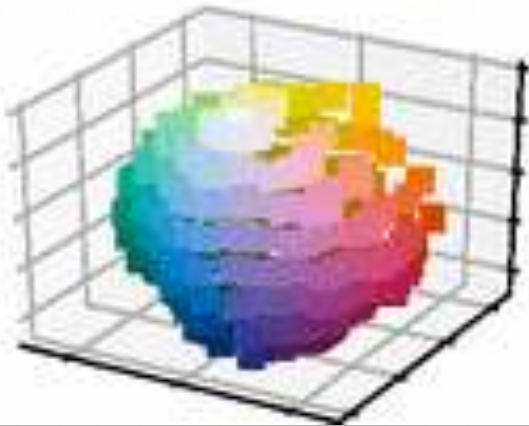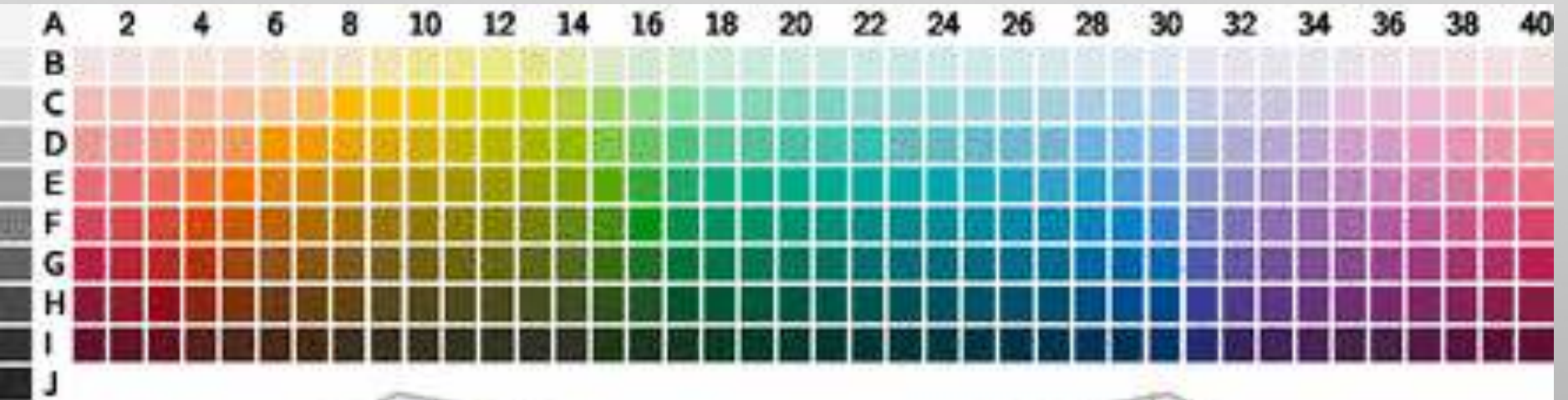

Credit: Aldebaran

Devdatt Dubhashi
AI and Data Science Division
Chalmers University
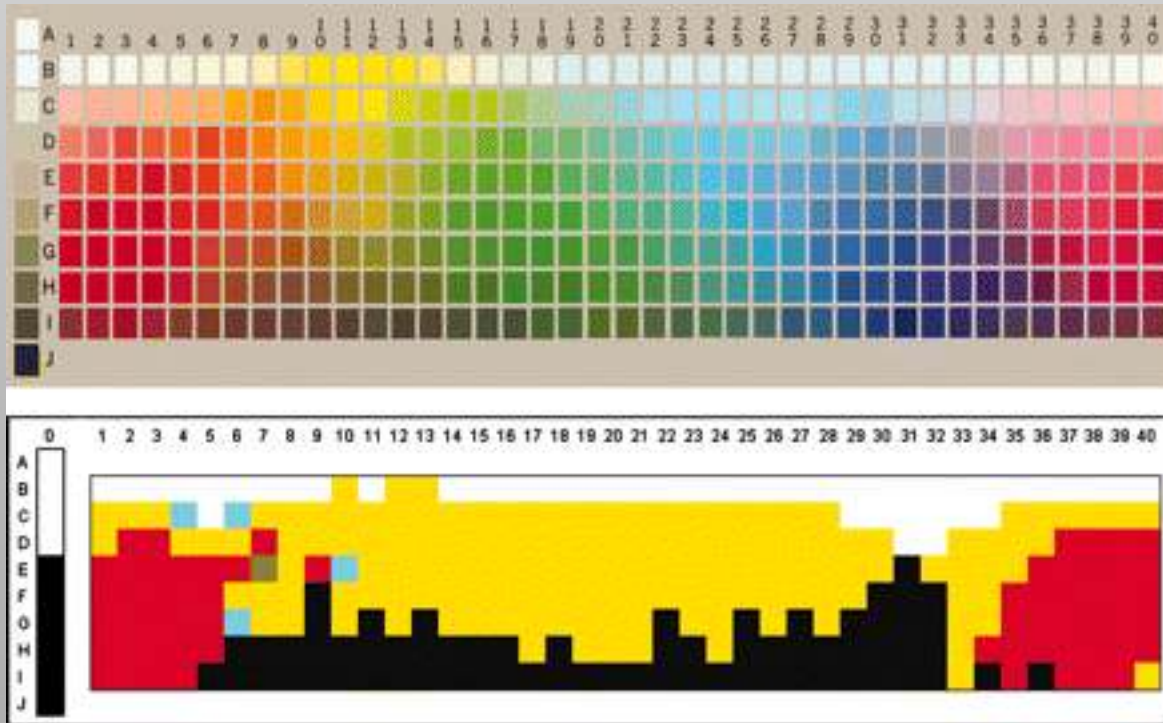
11/28/18

Mikael Kågebäck, Chalmers CSE

1

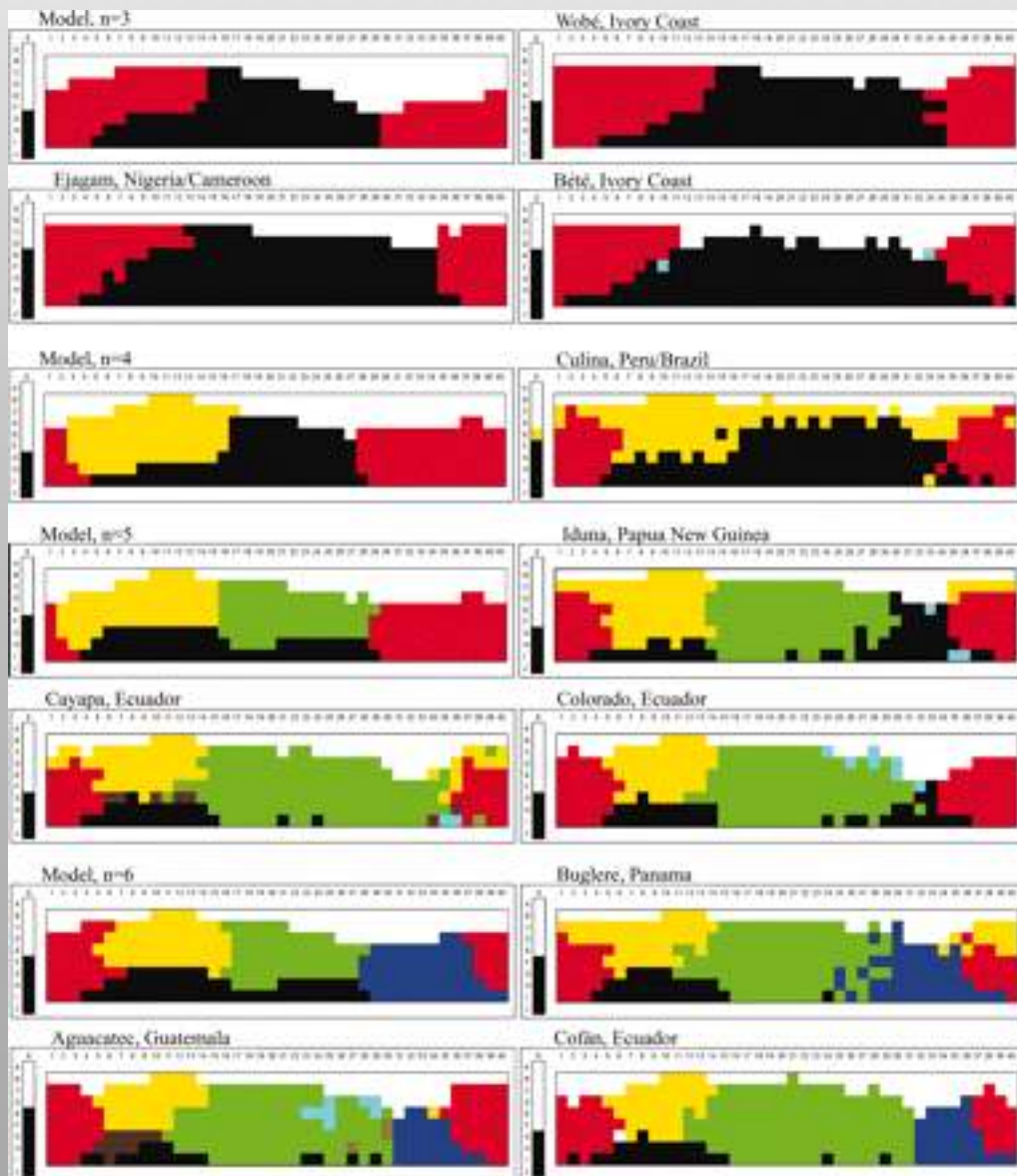# Are Colours Universal?

WCS Stimulus Palette

World Colour Survey

Language as Efficient Communication

- Communication over a noisy channel (Shannon)

- Informativeness

- Communication Efficiency versus

- Cognitive Load

- Rosch (1999, p. 190): semantic categories tend to "provide maximum information with the least cognitive effort."

Model, n=3   Wobé, Ivory Coast

Ejagam, Nigeria/Cameroon   Bété, Ivory Coast

Model, n=4   Culina, Peru/Brazil

Model, n=5   Iduna, Papua New Guinea

Cayapa, Ecuador   Colorado, Ecuador

Model, n=6   Buglere, Panama
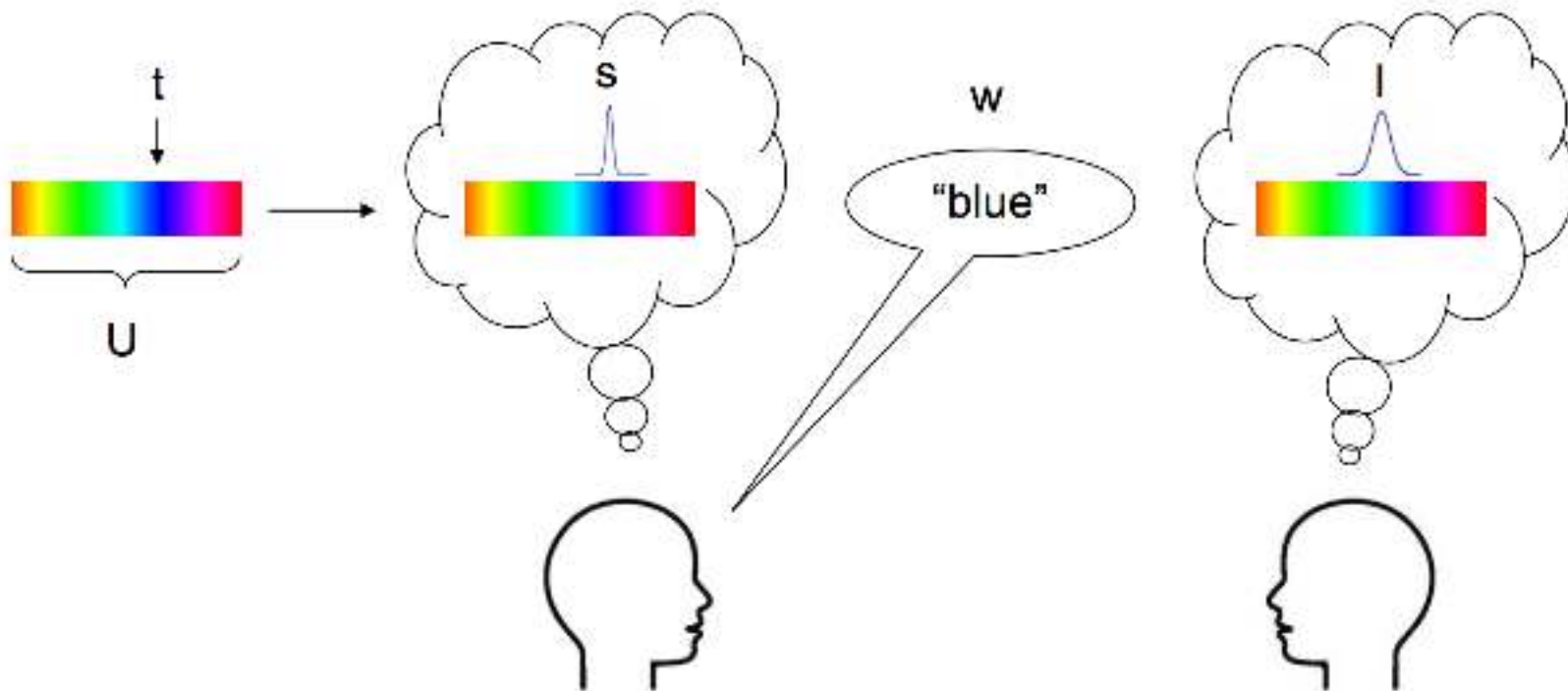
Aguacatec, Guatemala   Cofán, Ecuador

Regier T, Kemp C, Kay P. 2015. Word meanings across languages support efficient communication. In *The Handbook of Language Emergence*, ed. B MacWhinney, W O'Grady

Shannon Information Theory
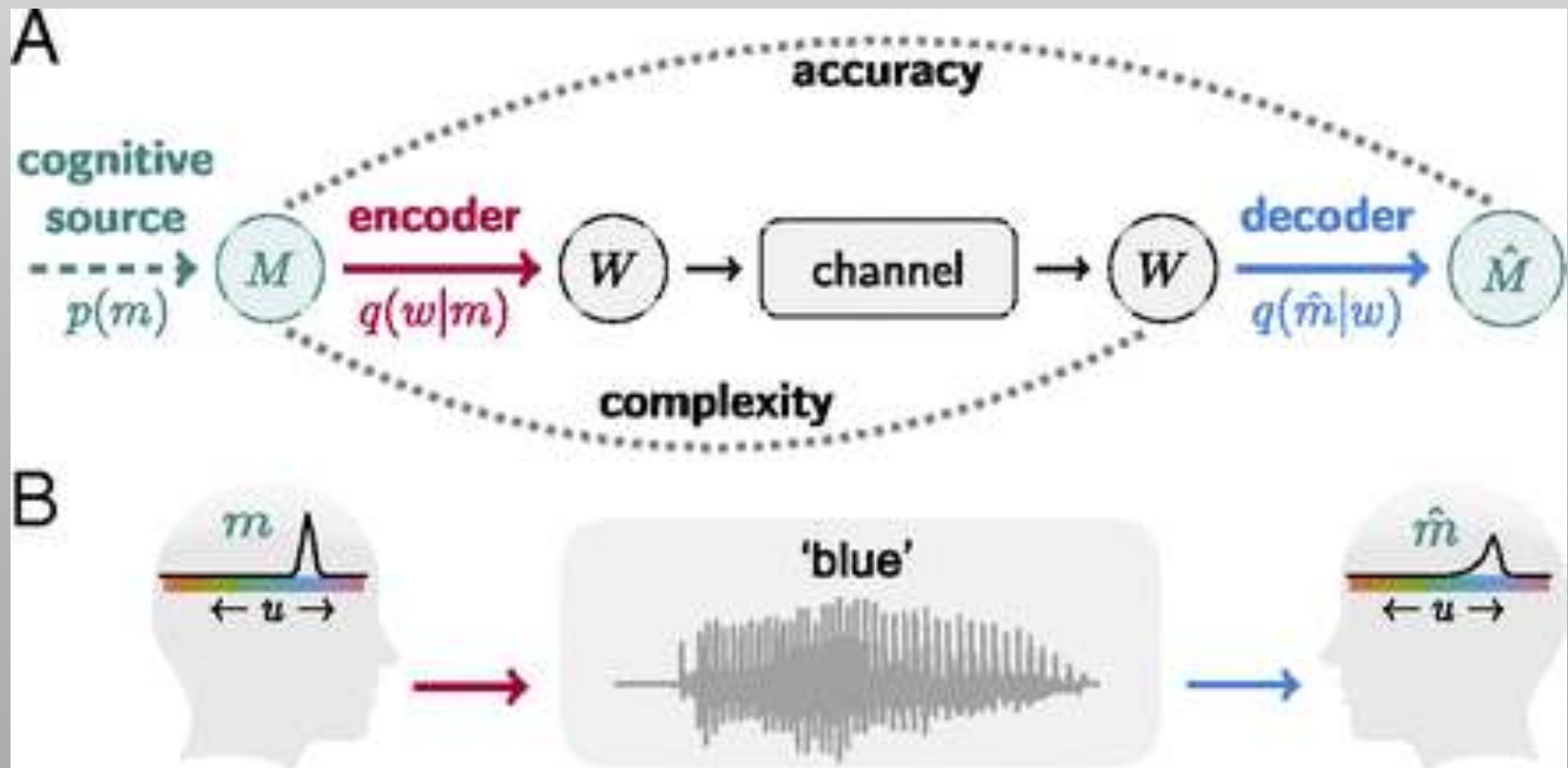
Information Theoretic View

$$D(s\|l) = \sum_{i \in U} s(i) \log_2 \frac{s(i)}{l(i)} = \log_2 \frac{1}{l(t)} = -\log_2(l(t))$$
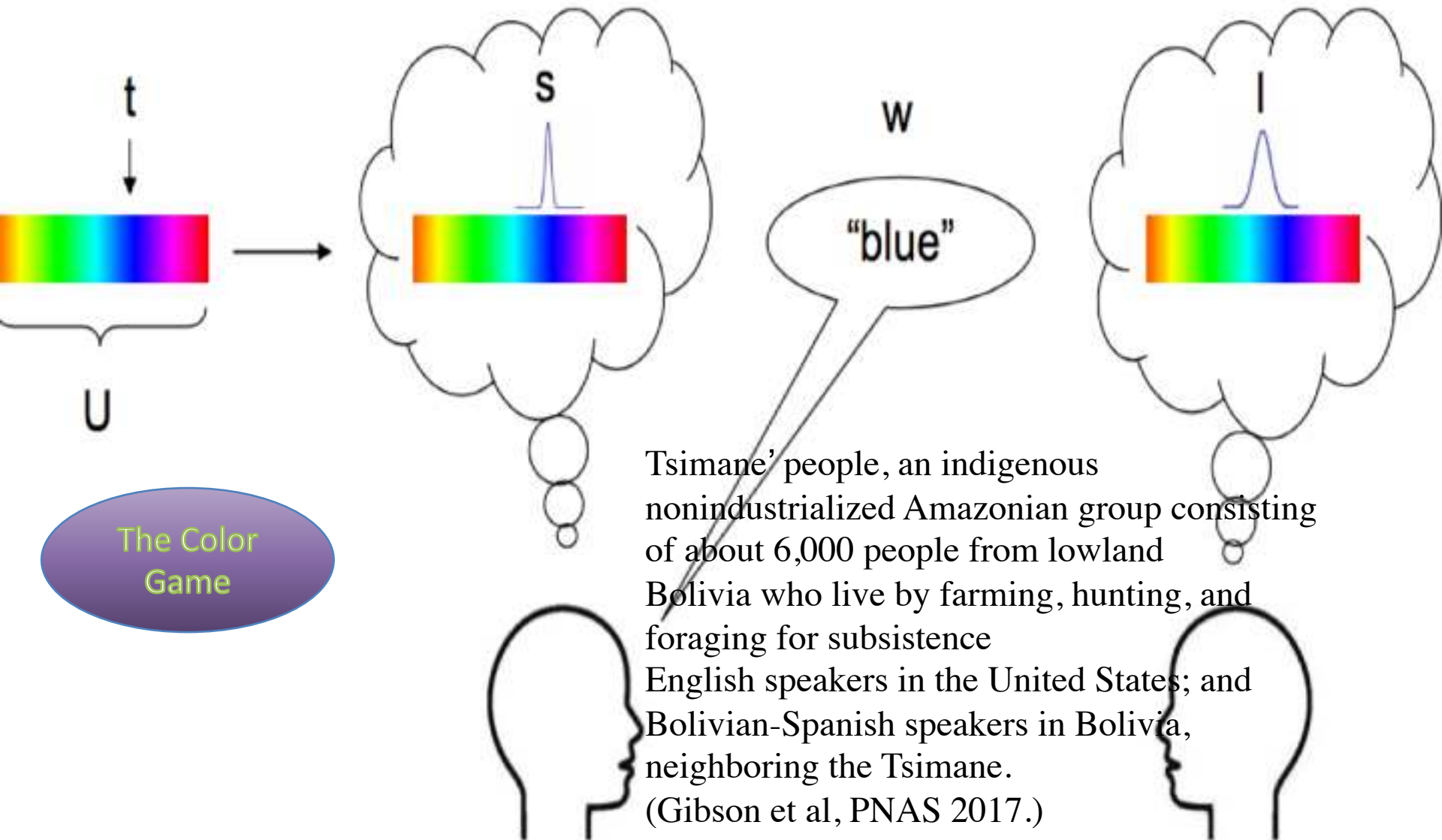
Tsimane' people, an indigenous nonindustrialized Amazonian group consisting of about 6,000 people from lowland Bolivia who live by farming, hunting, and foraging for subsistence

English speakers in the United States; and Bolivian-Spanish speakers in Bolivia, neighboring the Tsimane.

(Gibson et al, PNAS 2017.)

Reinforcement Learning

Weak signal

Can be unstable

internal state

reward
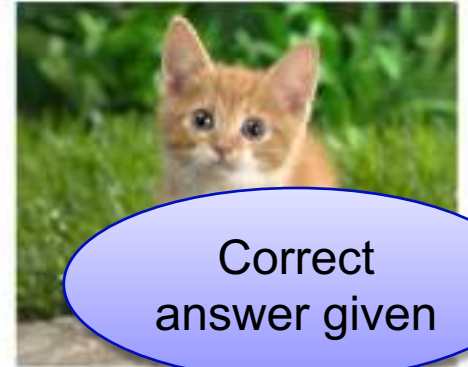
environment

action

No Labels needed

Flexible

Biologically plausible

observation
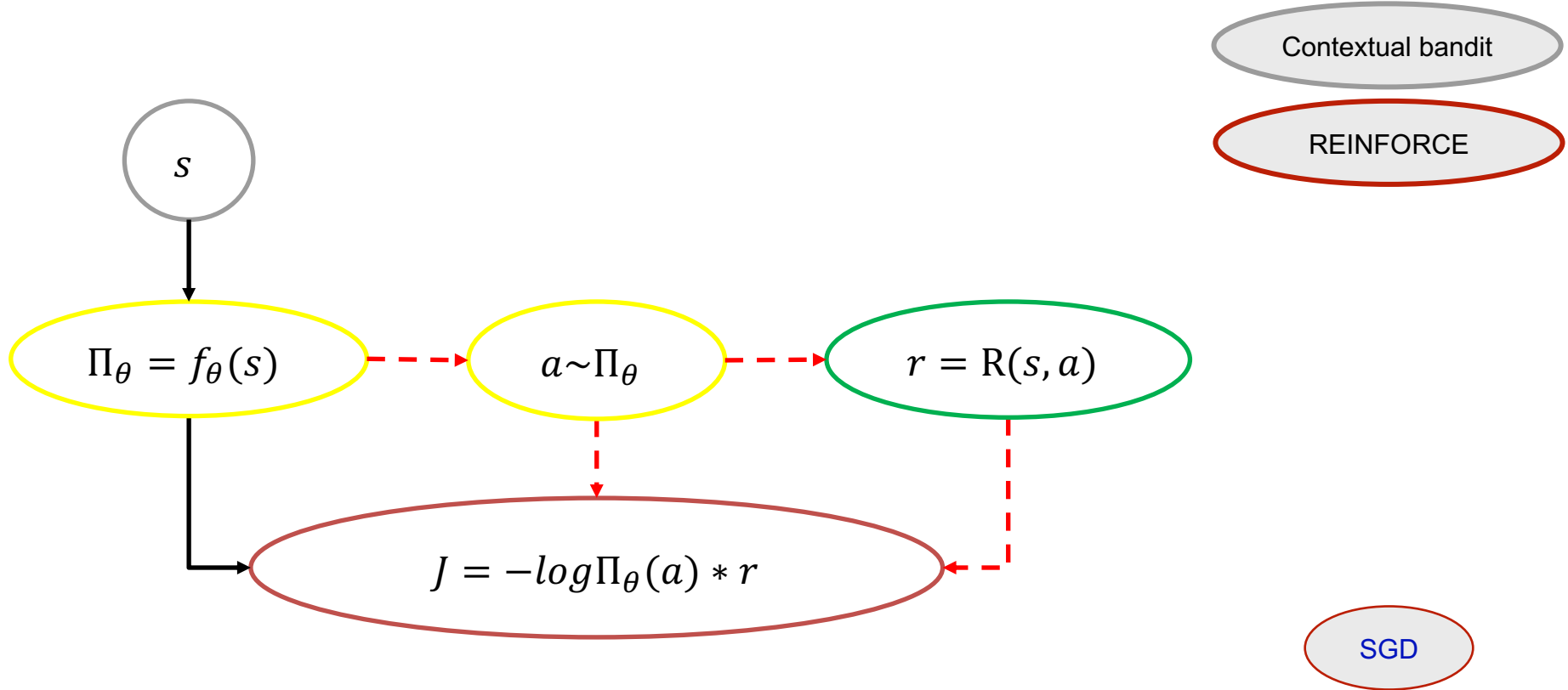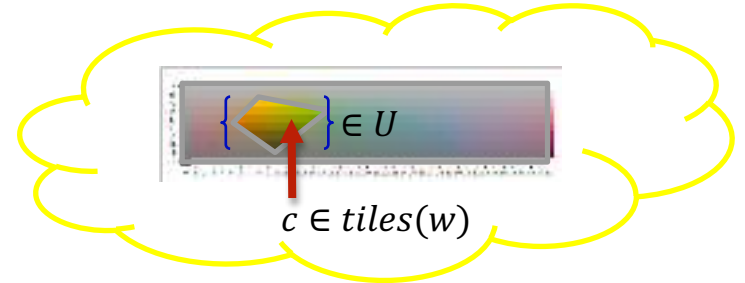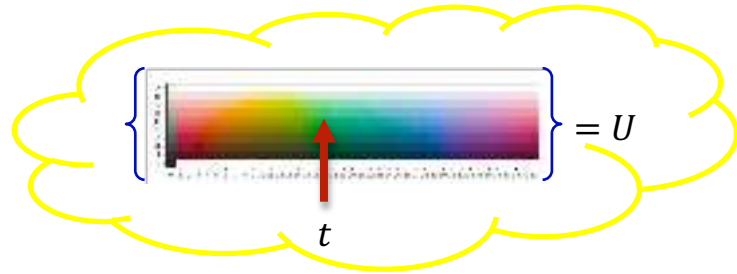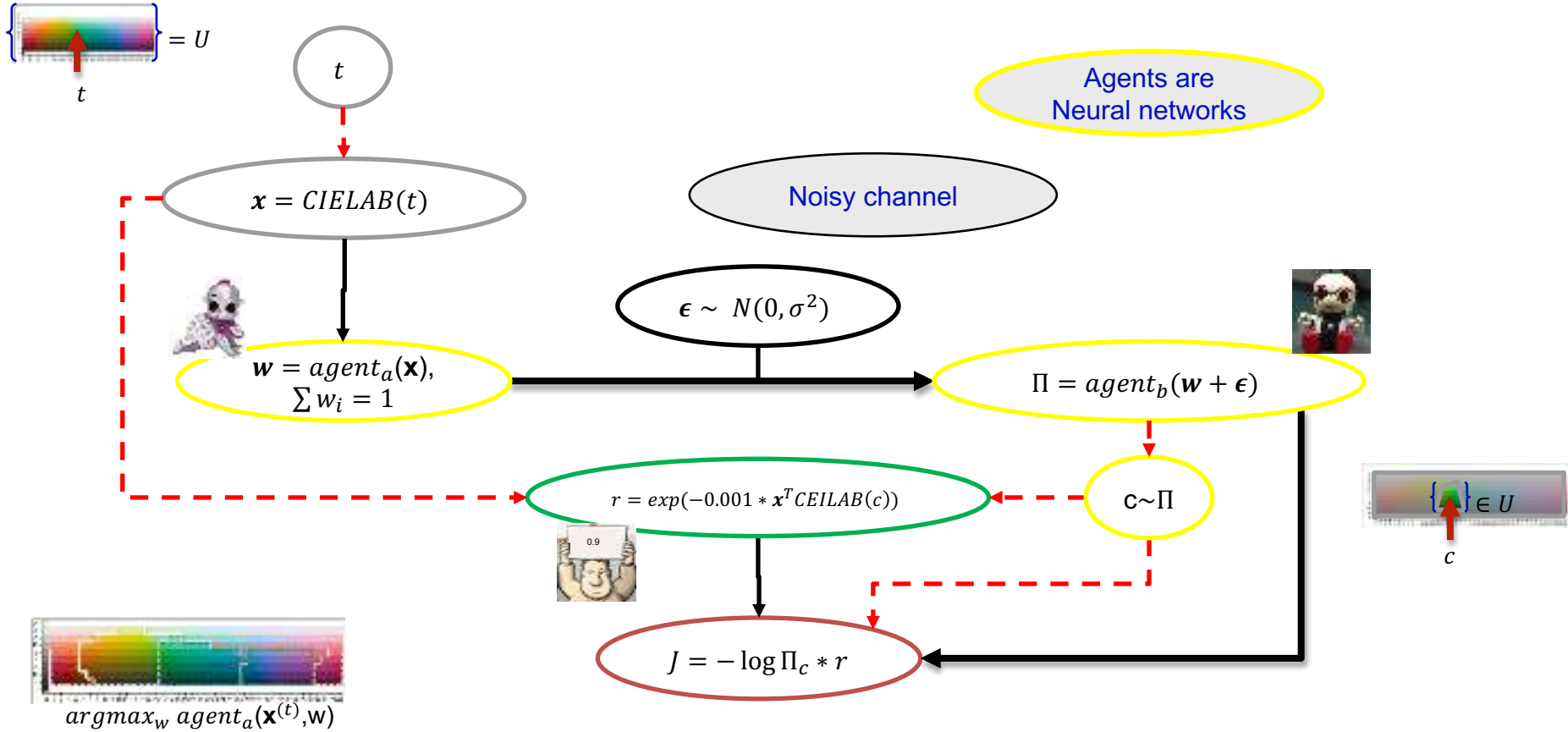
Information Loss

Efficient Communication

Complexity of language

CIELAB CC
Random
WCS languages mean
RL
WCS languages

KL Loss

Color terms used
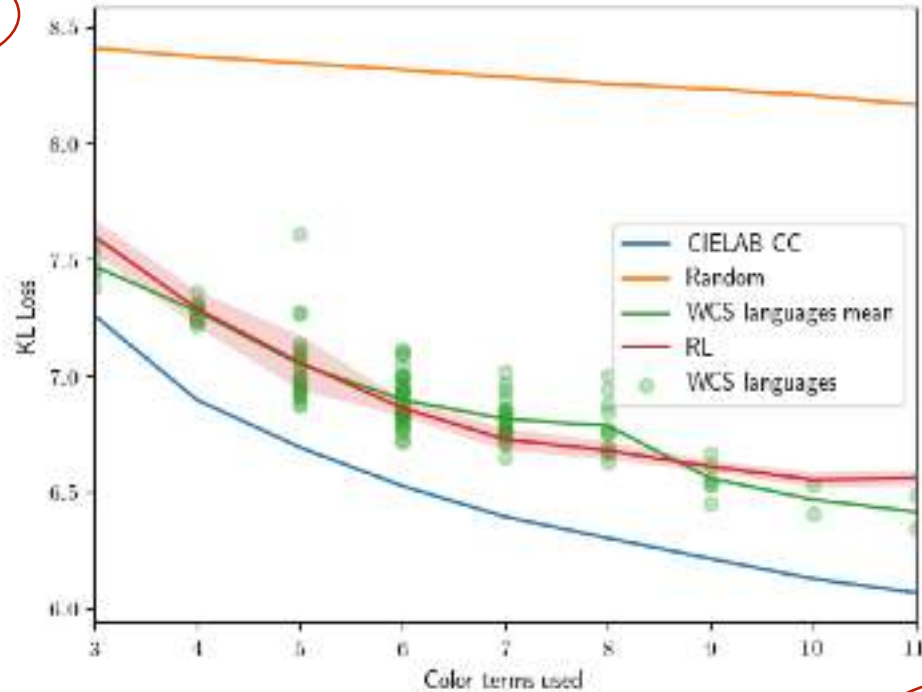
Table 3.1.1: **Comparison of the human languages in WCS to generated languages using Rand index. Abbreviations used in table column headers: H=human, RL=reinforcement learning, and R=random**

Terms	H-H	RL-RL	H-RL	H-R
3	0.701	0.273	0.173	0.000
4	0.452	0.337	0.167	0.000
5	0.476	0.373	0.223	0.000
6	0.528	0.537	0.277	0.000
7	0.472	0.593	0.292	0.000
8	0.471	0.518	0.281	0.000
9	0.584	0.510	0.321	0.000
10	0.718	0.549	0.316	0.000
11	0.472	0.543	0.309	0.000
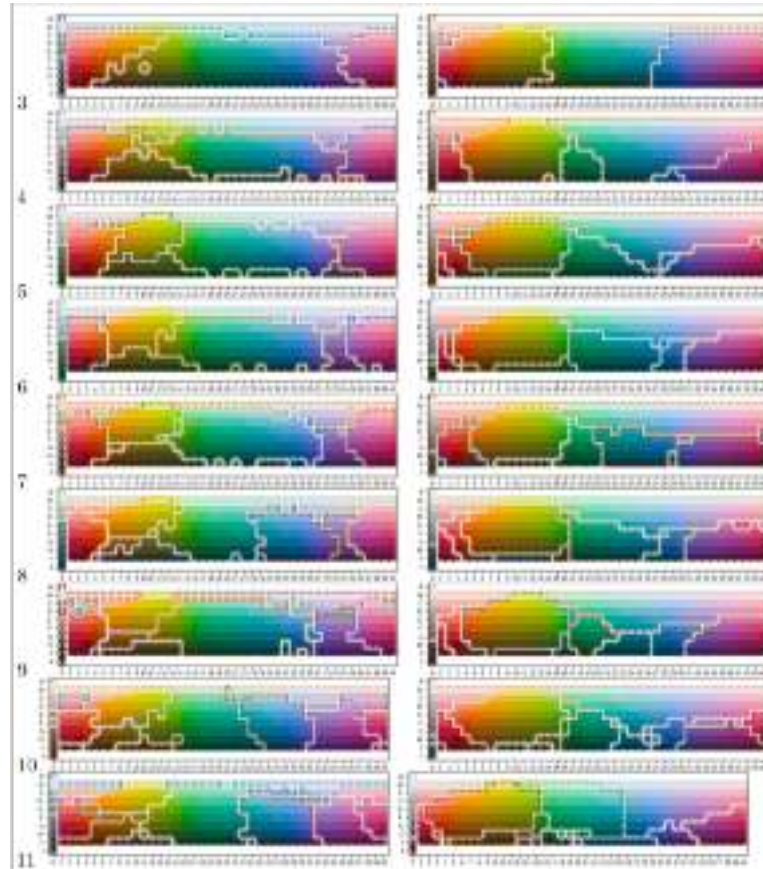
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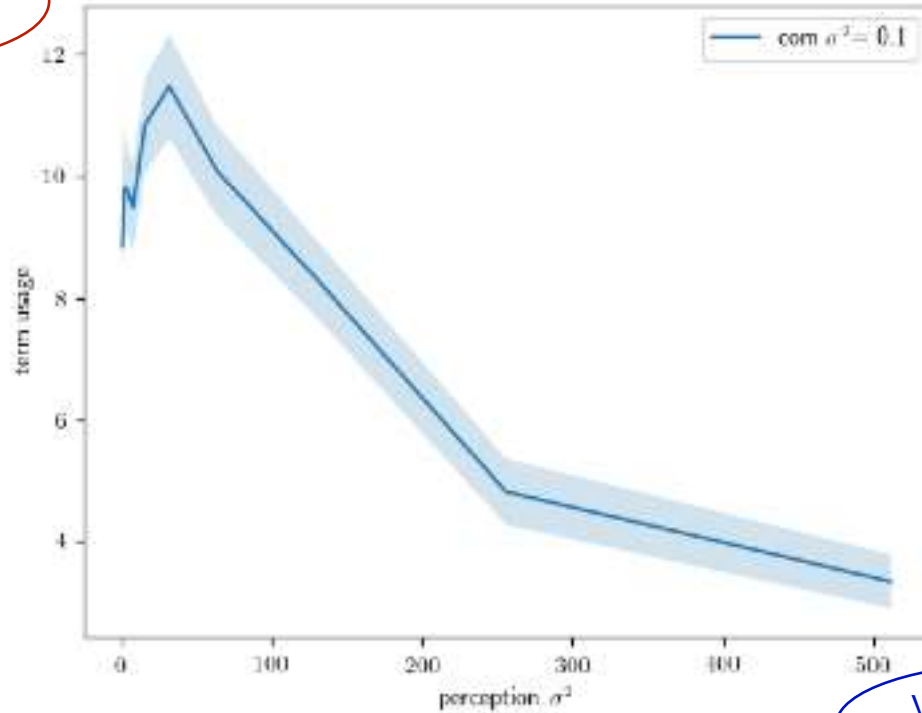
Variability in the environment

Language evolution over time

4 terms

5 terms

7 terms
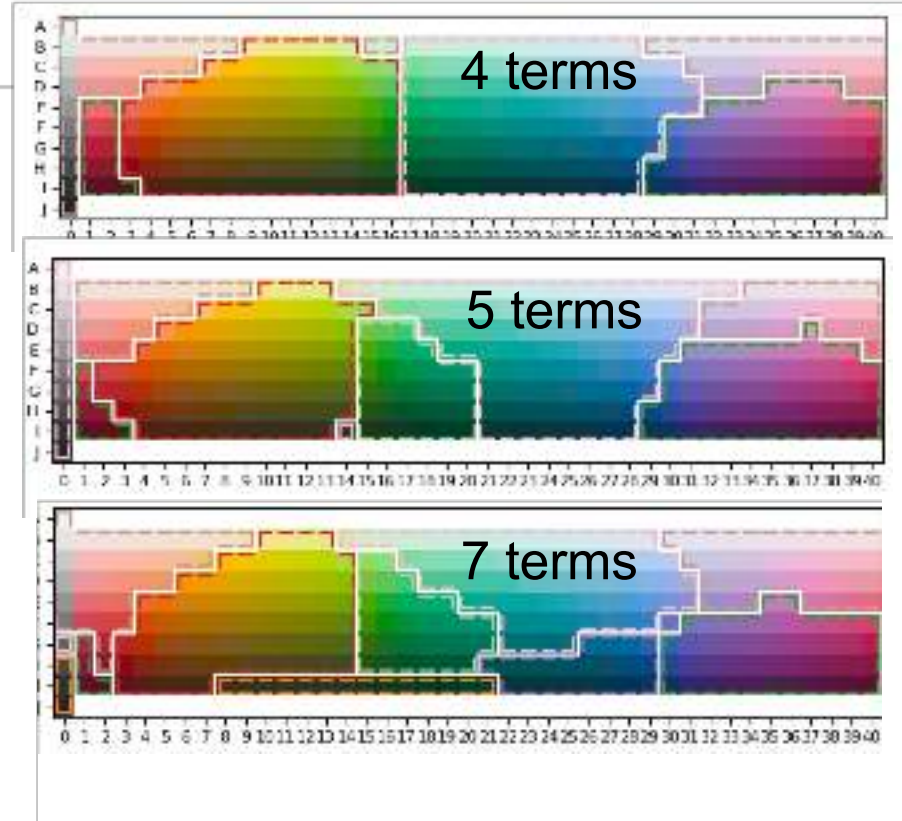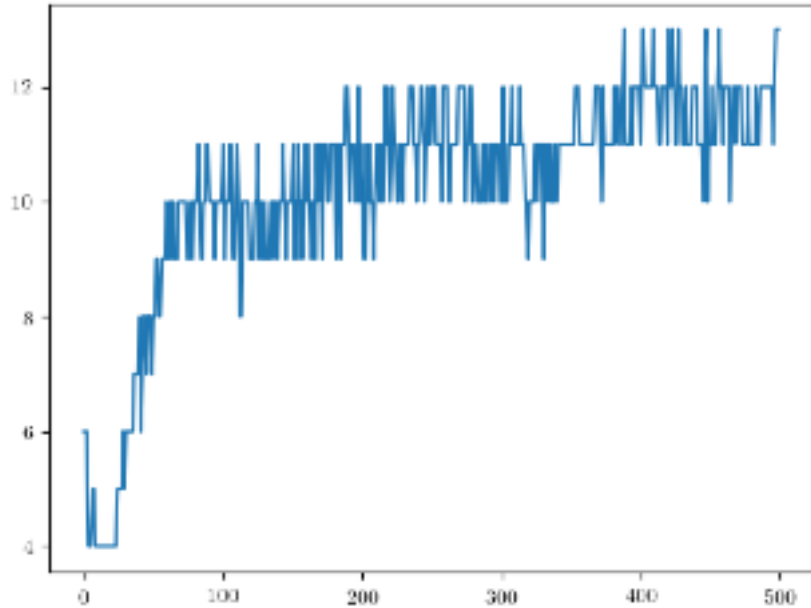
Concluding remarks: learning (a language) to communicate efficiently

Mikael Kågebäck[1], Devdatt Dubhashi[1], Asad Sayeed[2]

[1]Chalmers University of Technology, CSE
[2]University of Gothenburg, FLoV, CLASP

CHALMERS | GÖTEBORGS UNIVERSITET

Borges

An Argentinian philosopher and fiction writer. One of his stories mentions 'a certain Chinese Encyclopedia', the *Celestial Emporium of Benevolent knowledge.* It contains a classifcation of animals.

- those that belong to the emperor
- embalmed ones
- those that are trained
- suckling pigs
- mermaids
- fabulous ones
- stray dogs

Borges

. . . actually, it goes on.

- those that are included in the present classification
- those that tremble as if they are mad
- innumerable ones
- those drawn with a very fine camelhair brush
- others
- those that have just broken a flower vase
- those that from a long way off look like flies

Meaning

Think of lexical meaning as a kind of an amorphous blob.

(Lynda Benglis - New Museum)

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Previous efforts to find a formal, universal ontology of features failed. . .

Meaning

. . . and yet human speech communities manage to come up with common lexical structure that everyone can more or less understand.

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A partitioning of the space, if you will.

The case for colour

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Do we have common partitionings across languages?

Colour is. . .

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  - A function of the number of "main" colour words.
  - i.e. languages with three colour words will have the same colour words, languages with four will have those three, etc.

Our research question:
How do speech communities converge on a partition of semantic spaces?

What we can show via colour

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  - Model improvement? Lightness variable in CIELAB space needs to be weighted differently?
- RL maps share behaviour of human maps in terms of partition stability as colour term nubmers increase.
  - RL agents tend to sub-partition existing partitions rather than rework the partitions as they use more words.

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3. Control over high-level variables: change noise parameter to represent environmental conditions.

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  Hypothesizing expected behaviour in corpora.

Thanks!