Statistical physics approach to social dynamics

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What is statistical physics?

- Statistical physics investigates how the collective behavior of a large number of microscopic interacting particles gives rise to macroscopic phenomena

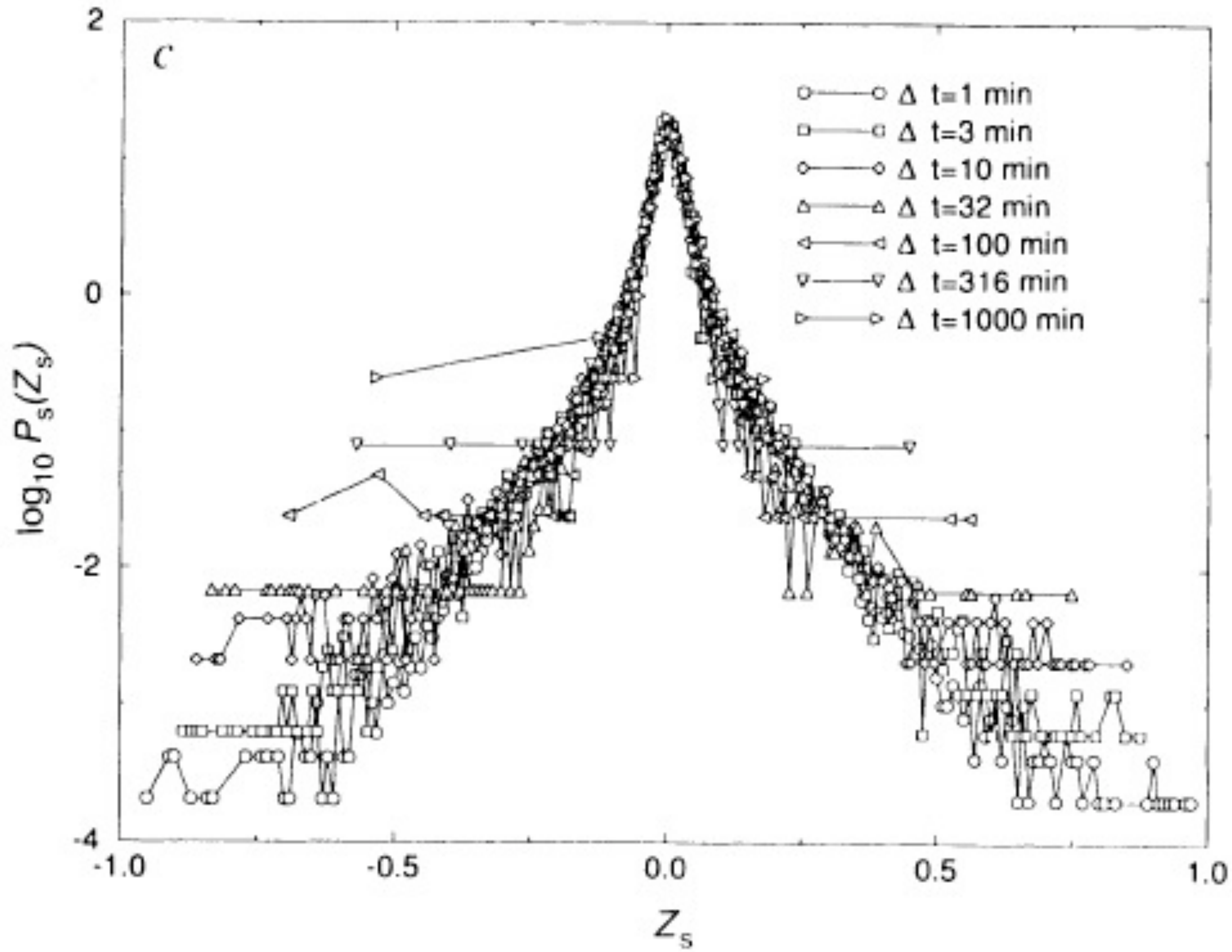
- Examples: gases, magnets, ...

- Not only in the physical domain, but also in the social domain

many nontrivial regularities emerge out of apparently of erratic behavior.

Regularities in social systems

- patterns in price fluctuations in finance



Regularities in social systems

- the network structure of the internet

Data revolution

- Huge amount of data available: enormous databases collect data about many human/social activities (credit cards, phone calls, marketing data, activity on the internet).

- Computers make the analysis of these data possible.

- Entire new social phenomena started in the past few decades: internet, electronic financial markets, mobile telephones, etc.

$\boxed{\text{Data-driven Computational Social Science}}$

SOCIAL SCIENCE

Computational Social Science

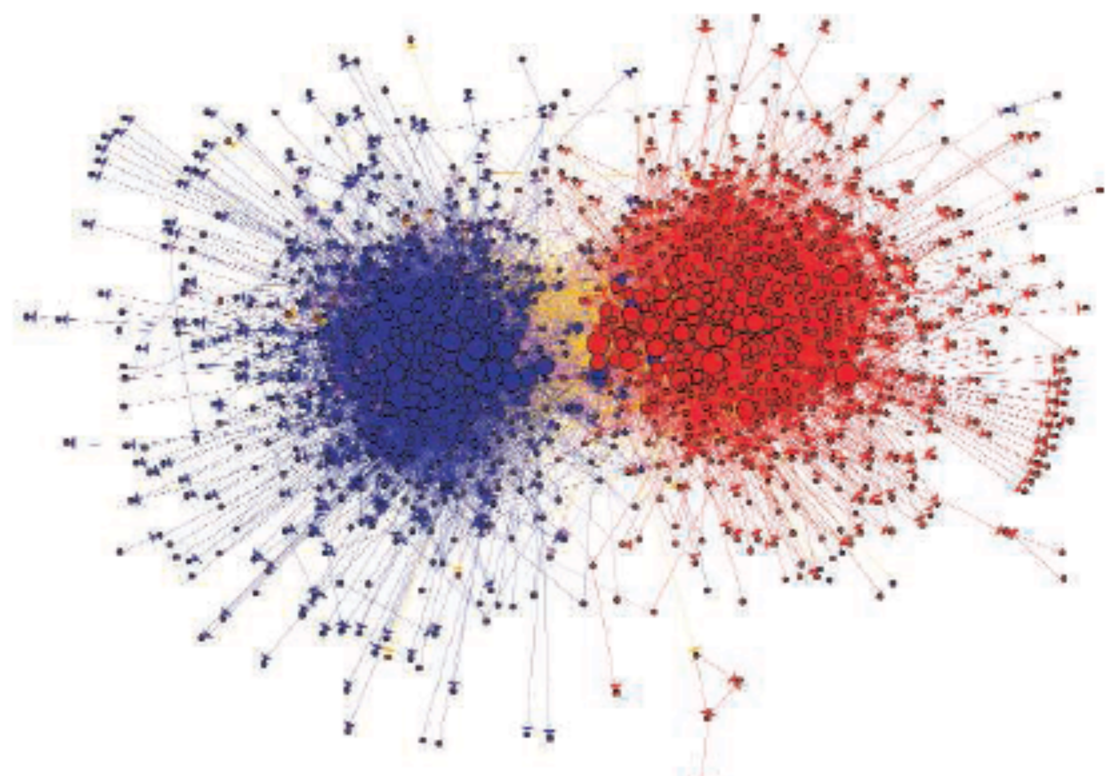
A field is emerging that leverages the capacity to collect and analyze data at a scale that may reveal patterns of individual and group behaviors.

David Lazer,[1] Alex Pentland,[2] Lada Adamic,[3] Sinan Aral,[2,4] Albert-László Barabási,[5] Devon Brewer,[6] Nicholas Christakis,[1] Noshir Contractor,[7] James Fowler,[8] Myron Gutmann,[3] Tony Jebara,[9] Gary King,[1] Michael Macy,[10] Deb Roy,[2] Marshall Van Alstyne[2,11]

We live life in the network. We check our e-mails regularly, make mobile phone calls from almost any location, swipe transit cards to use public transportation, and make purchases with credit cards. Our movements in public places may be captured by video cameras, and our medical records stored as digital files. We may post blog entries accessible to anyone, or maintain friendships through online social networks. Each of these transactions leaves digital traces that can be compiled into comprehensive pictures of both individual and group behavior, with the potential to transform our understanding of our lives, organizations, and societies.

The capacity to collect and analyze massive amounts of data has transformed such fields as biology and physics. But the emergence of a data-driven "computational social science" has been much slower. Leading journals in economics, sociology, and political science show little evidence of this field. But computational social science is occurring—in Internet companies such as Google and Yahoo, and in government agencies such as the U.S. National Security Agency. Computational social science could become the exclusive domain of private companies and government agencies. Alternatively, there might emerge a privileged set of academic researchers presiding over private data from which they produce papers that cannot be critiqued or replicated. Neither scenario will serve the long-term public interest of accumulating, verifying, and disseminating knowledge.

What value might a computational social science—based in an open academic environment—offer society, by enhancing understanding of individuals and collectives? What are the



Data from the blogosphere. Shown is a link structure within a community of political blogs (from 2004), where red nodes indicate conservative blogs, and blue liberal. Orange links go from liberal to conservative, and purple ones from conservative to liberal. The size of each blog reflects the number of other blogs that link to it. [Reproduced from (*8*) with permission from the Association for Computing Machinery]

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Opinion/consensus dynamics

Starting from a random initial state

what is the effect of repeated interactions?

Ingredients:

- type of opinions (discrete/continuous,...)
- type of interactions
- connectivity patterns
- ......

Questions:

- Is consensus reached?
- What type of consensus?
- How many interactions are needed?

Consensus dynamics

PNAS

Behavioral dynamics and influence in networked coloring and consensus

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Edited by Brian Skyrms, University of California, Irvine, CA, and approved July 16, 2010 (received for review February 3, 2010)

We report on human-subject experiments on the problems of *coloring* (a social differentiation task) and *consensus* (a social agreement task) in a networked setting. Both tasks can be viewed as coordination games, and despite their cognitive similarity, we find that within a parameterized family of social networks, network structure elicits *opposing* behavioral effects in the two problems, with increased long-distance connectivity making consensus easier for subjects and coloring harder. We investigate the influence that subjects have on their network neighbors and the collective outcome, and find that it varies considerably, beyond what can be explained by network position alone. We also find strong correlations between influence and other features of individual subject behavior. In contrast to much of the recent research in network science, which often emphasizes network topology out of the context of any specific problem and places primacy on network position, our findings highlight the potential importance of the details of tasks and individuals in social networks.

model of individual behavior, when run in simulation on our networks, can qualitatively capture this behaviorally observed phenomenon.

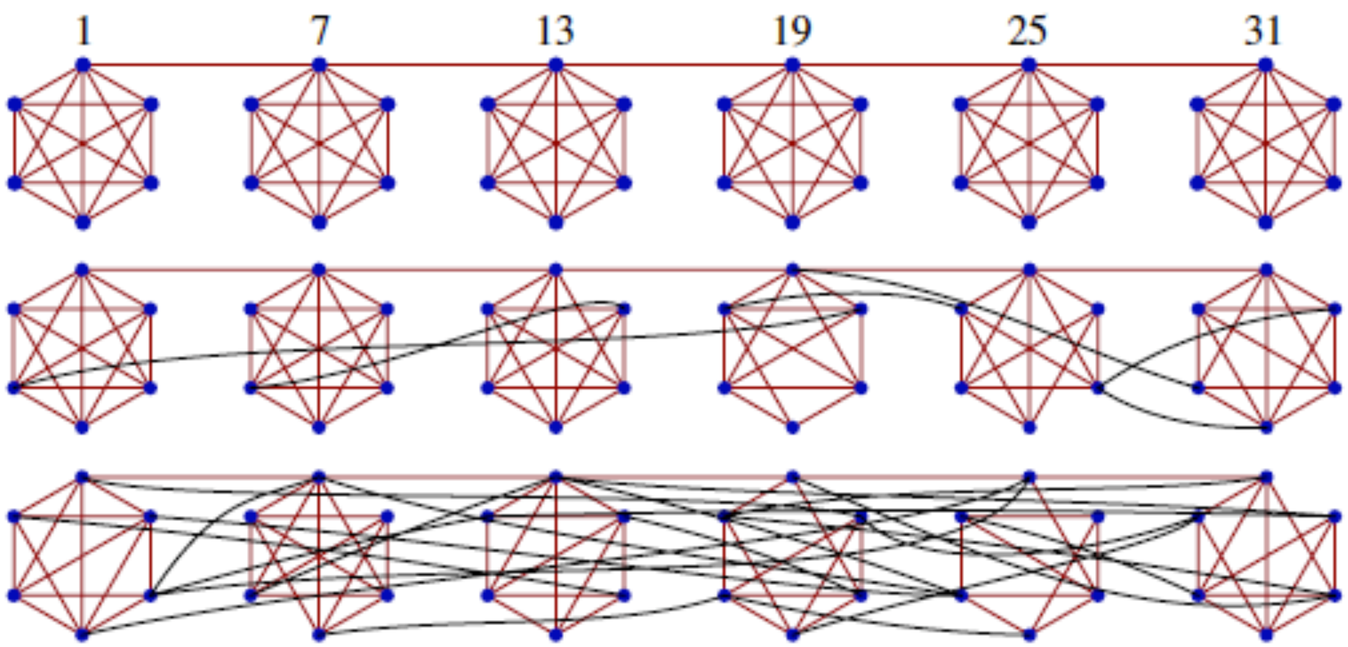
Turning to aspects of individual rather than collective behavior, we also introduce natural notions of a player's *influence* on their neighbors and the outcome of an experiment, and study the amount and origin of such influences. We find that the variation in influence across players is beyond what can be explained by the variability in their network positions, and that this influence is only weakly correlated with topological properties of network position such as degree and centrality.

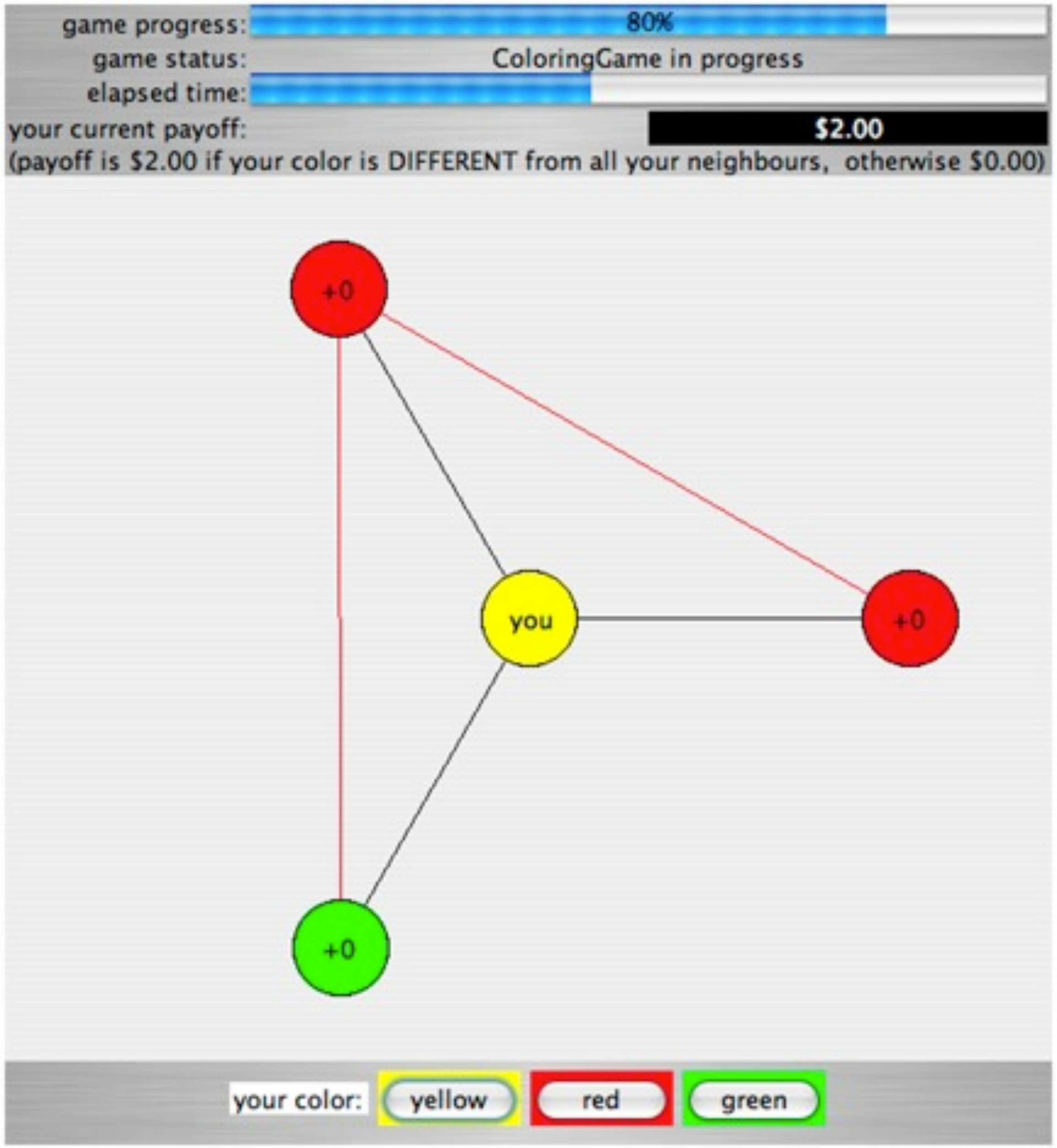
Taken together, our results highlight aspects of collective behavior in network science that have been considered before (2, 3), but are perhaps deemphasized recently in favor of purely structural studies: namely, the potential primacy of task and agent details in social networks.

Related Work

COMPUTER SCIENCES

Consensus dynamics





“Cultural” dynamics

“If people tend to become more alike in their beliefs, attitudes and behaviors when they interact, why do not all differences disappear?”

R. Axelrod, J. of Conflict Resolut., 41, 203 (1997).

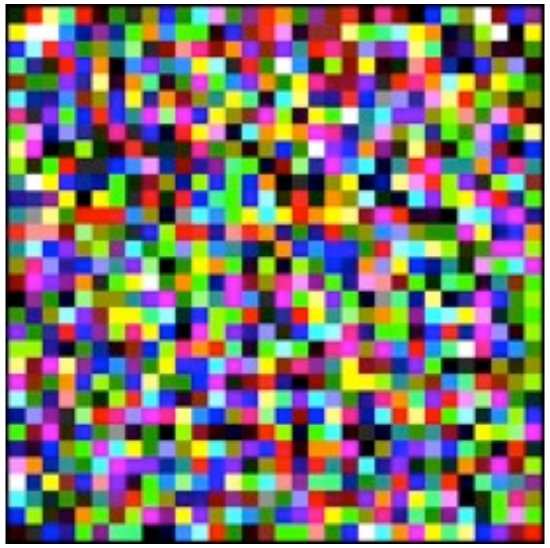
“Culture” is a set of several coupled features (variables).

Two basic ingredients:

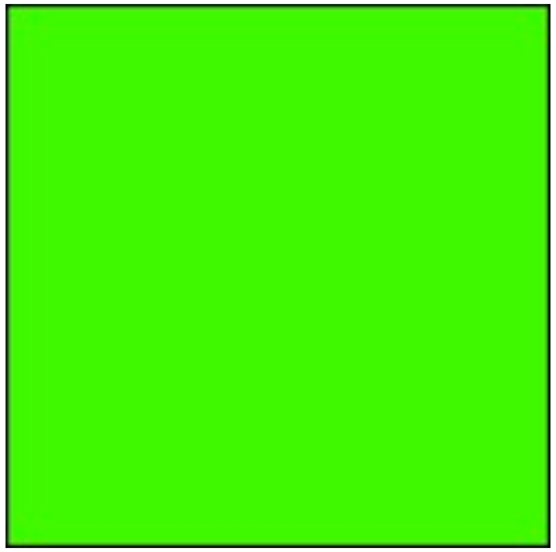
- Social Influence: interactions make individuals more similar
- Homophily: Likeliness of interactions grows with similarity

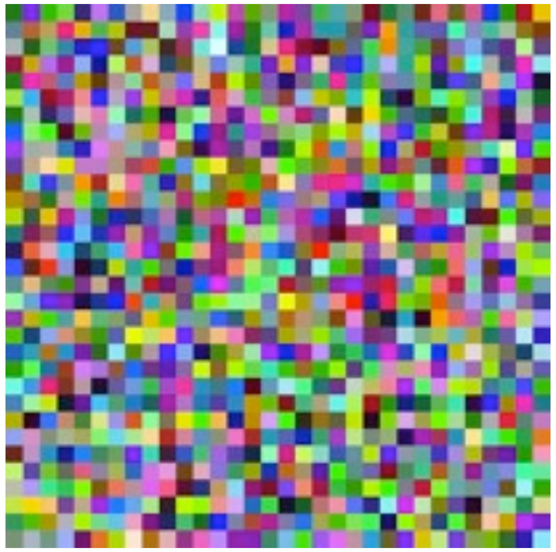
Fragmentation-consensus transition

The evolution depends on the number q of traits in the initial state

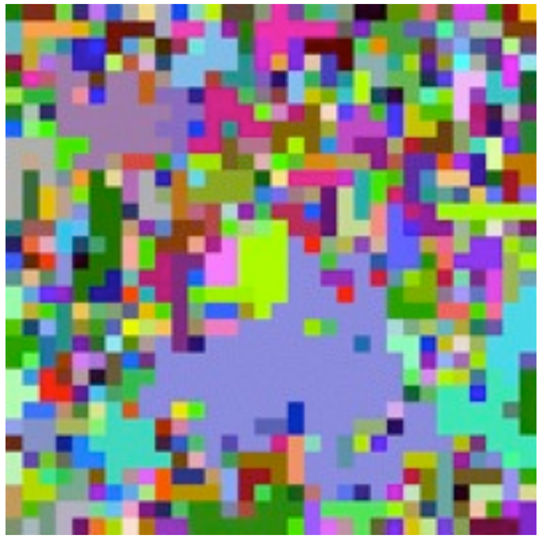


small q =
low initial
variability





large q =
high initial
variability



The Naming Game

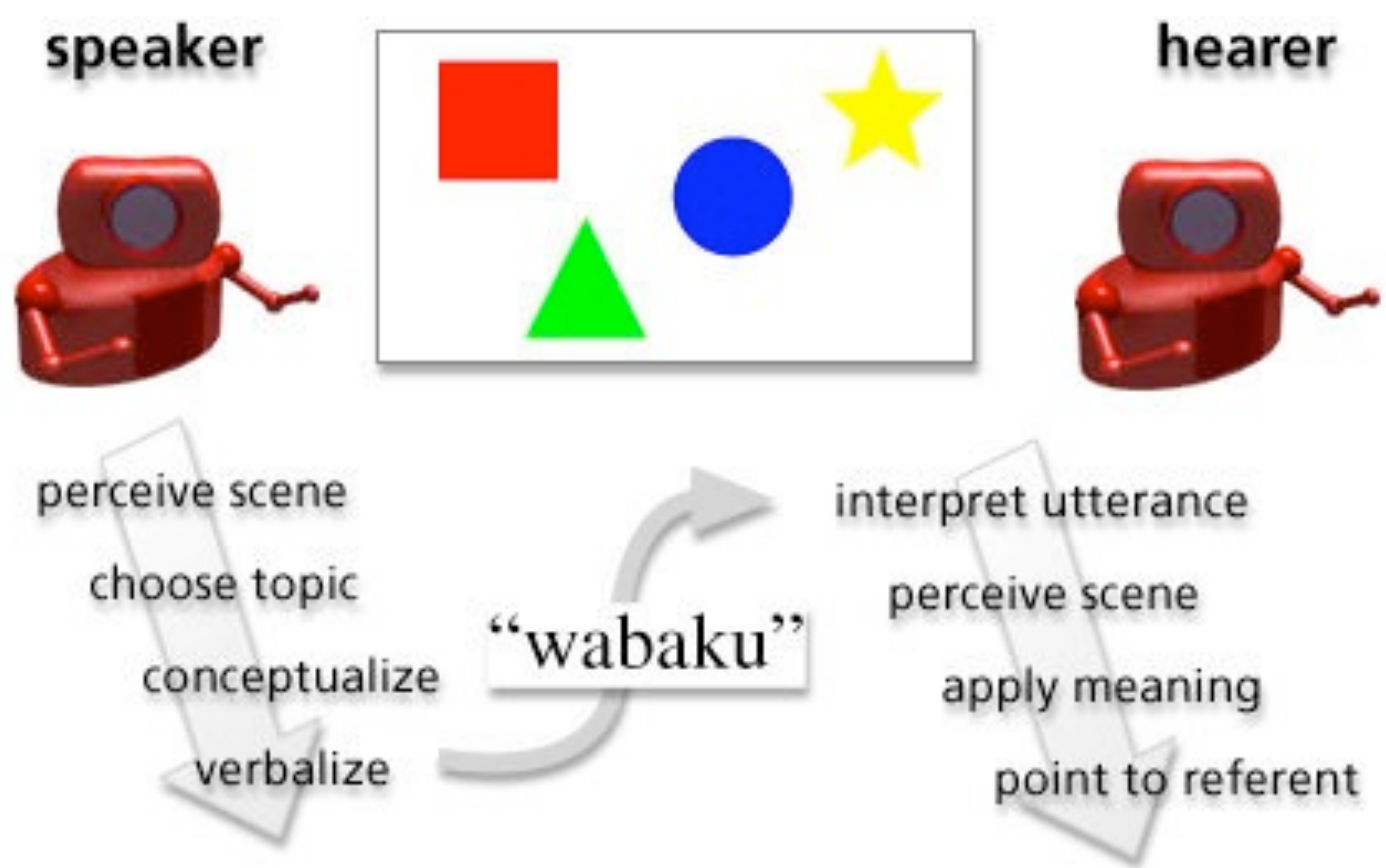
The Naming Game

Steels (1999)

How does a shared vocabulary arise among agents in a self-organized way?

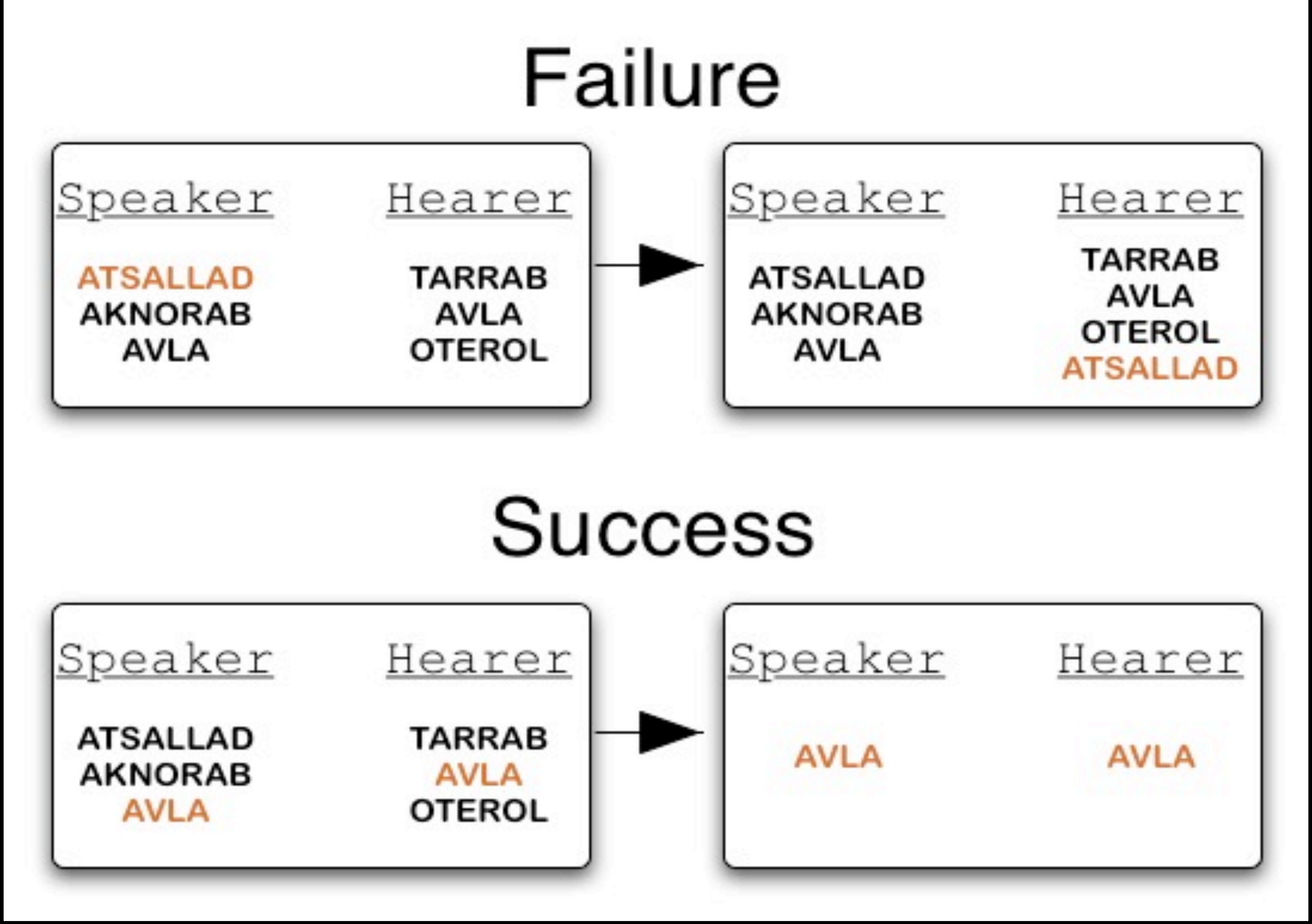
Shared vocabulary = shared mapping between words and meanings.

Agents develop privately their own vocabulary



Agents interact and vocabulary alignment is beneficial (mutual understanding)

The Naming Game

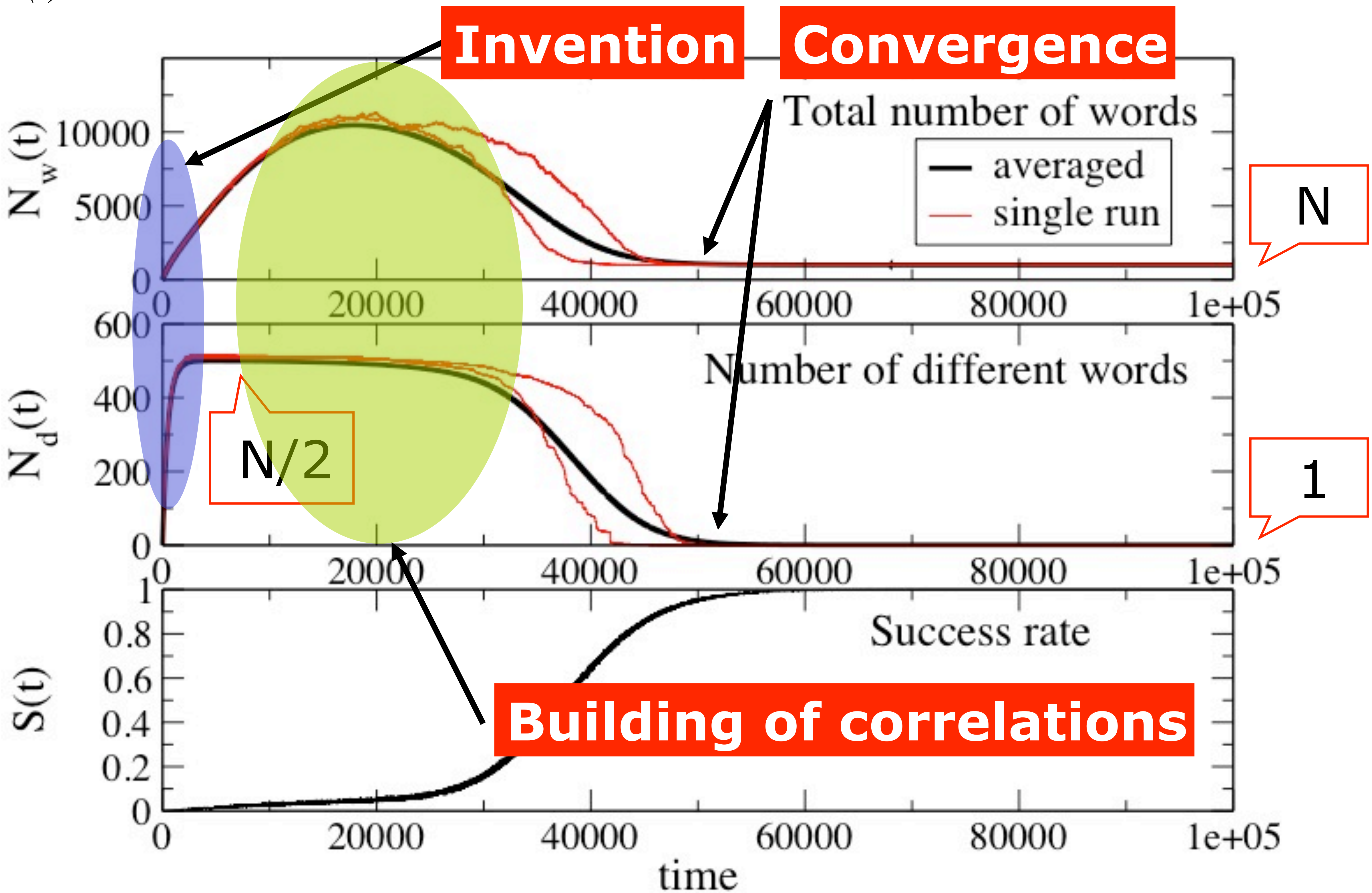


negotiation + memory + dynamic inventories

$N_w(t)$ = total number of words

$N_d(t)$ = number of different words

$S(t)$ = interaction success rate

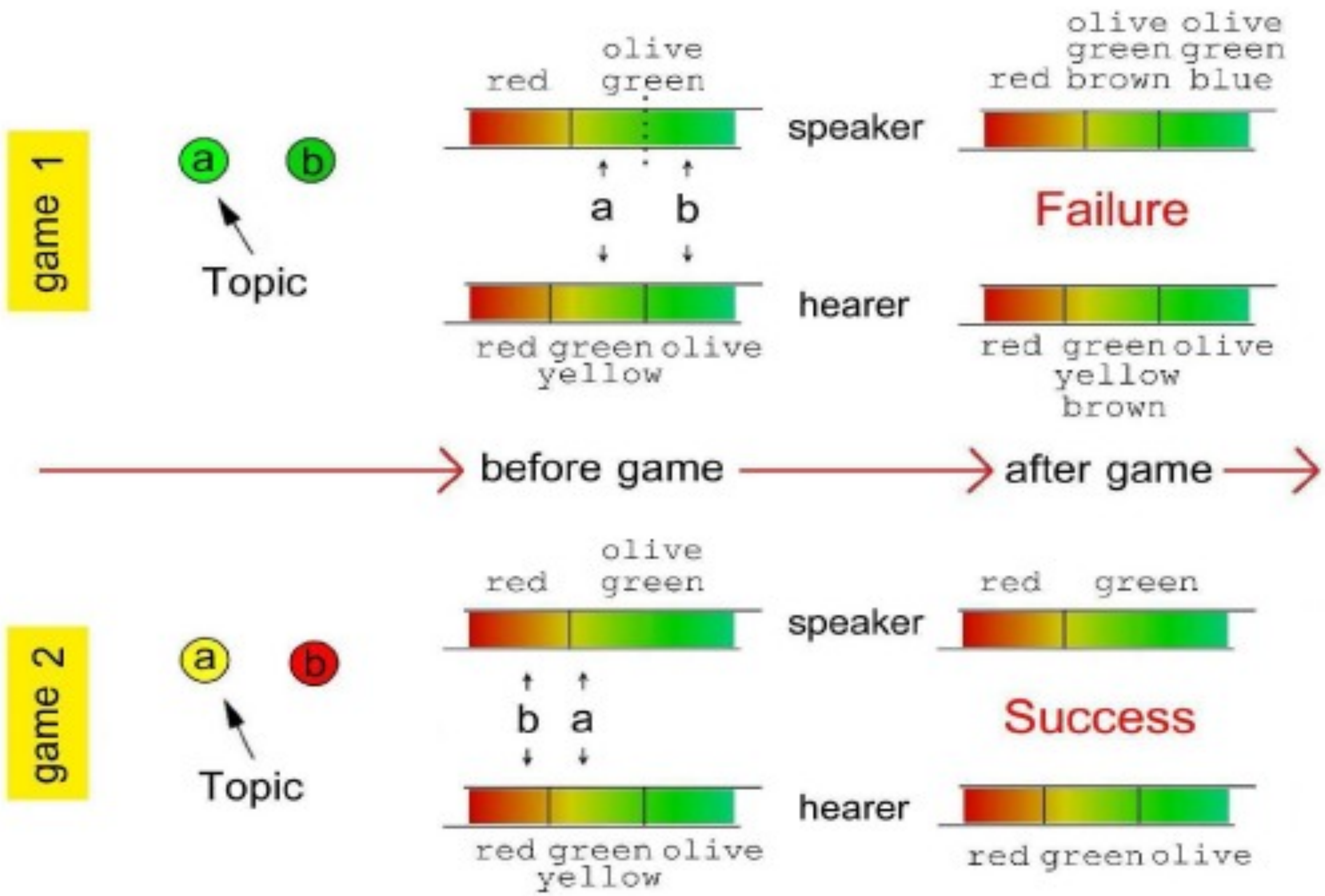


The Category Game

The category game

N individuals performing binary language games
Individual task: discriminate stimuli from a continuous [0:1] perceptual space

0 Real values on the interval [0, 1] 1

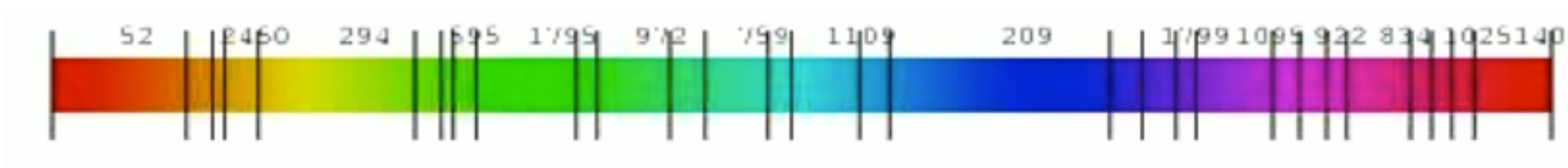


d_{min}

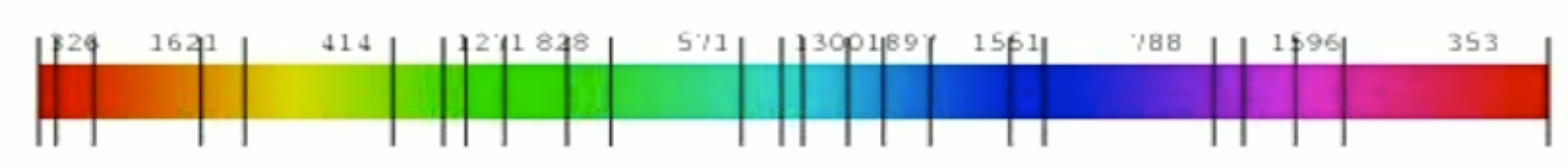
the minimum distance between two stimuli that can be distinguished by agents

A. Puglisi, A. Baronchelli and VL
"Cultural route to the emergence of linguistic categories"
Proc. Natl. Acad. Sci USA (PNAS) 105, 7936 (2008).

Evolution of Linguistic Categories



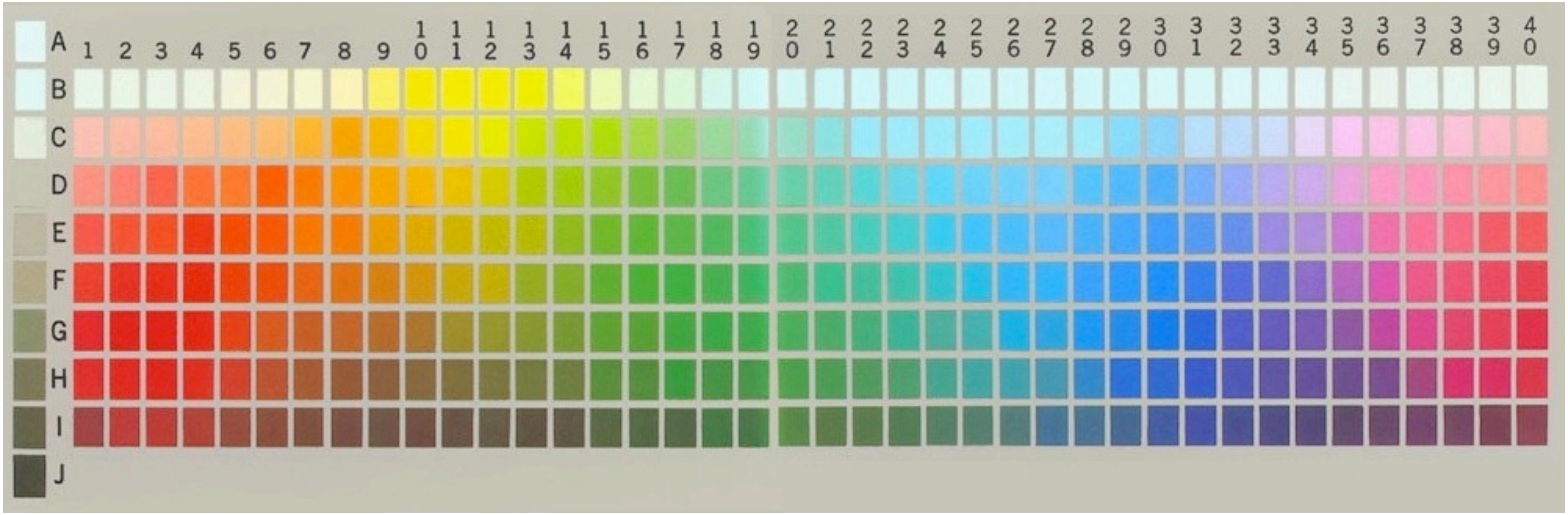
N=50, d_min=0.01



N=50, d_min=0.02

Comparison with real data

World color survey (WCS)



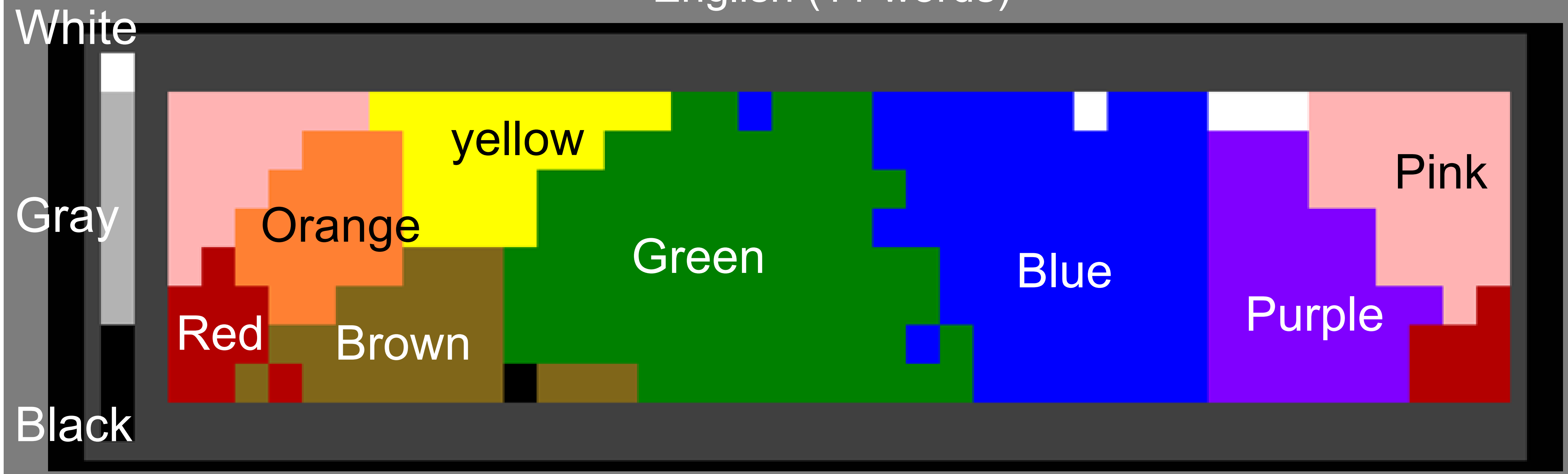
110 "preindustrialized" languages
24 "monolingual" speakers

speakers were asked to:

1. name each of the 330 munsell chips
2. indicate the best example(s) of each of his basic color terms

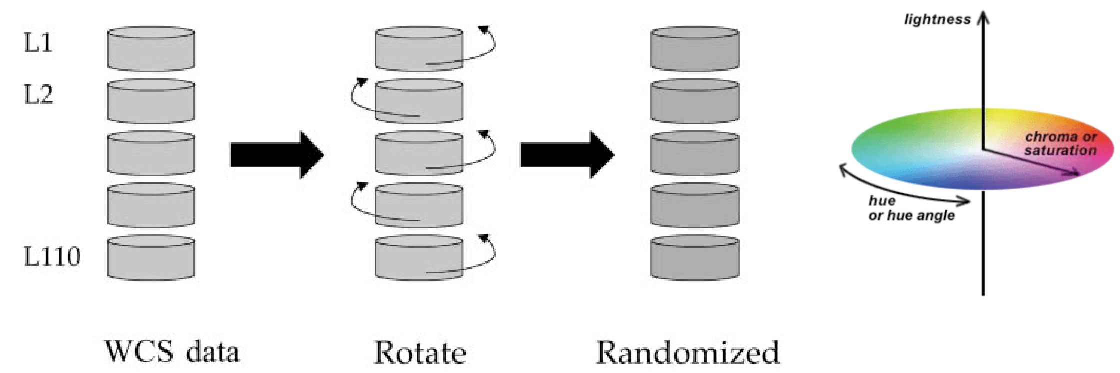
Basic Color Terms name all the colors:

English (11 words)

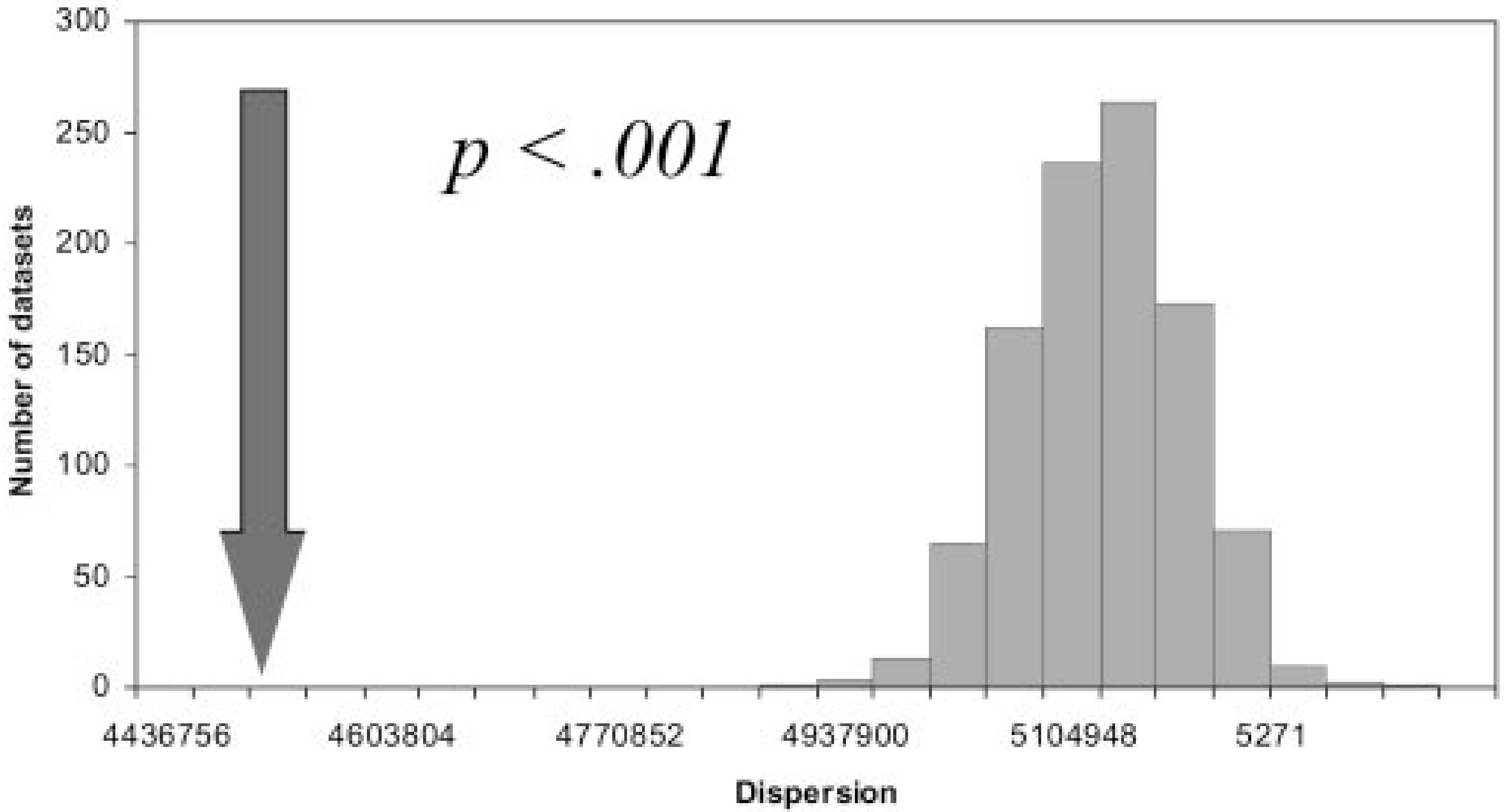


Courtesy of Lindsey & Brown (2006). *PNAS, 102.*

testing universality of color naming



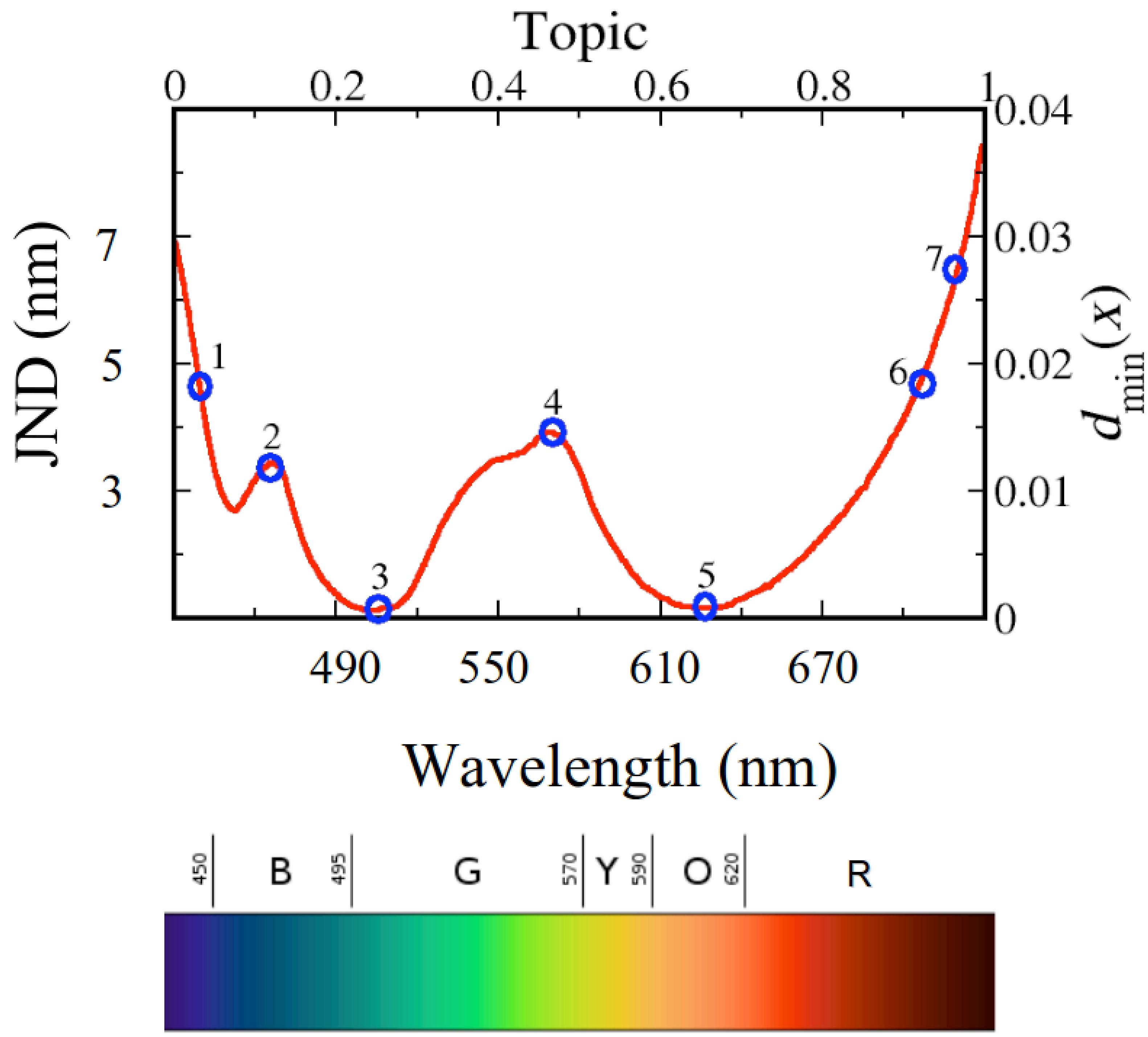
Human Case



$$D = \sum_{l,l^* \in WCS} \sum_{c \in l} \min_{c^* \in l^*} \text{distance}(c, c^*).$$

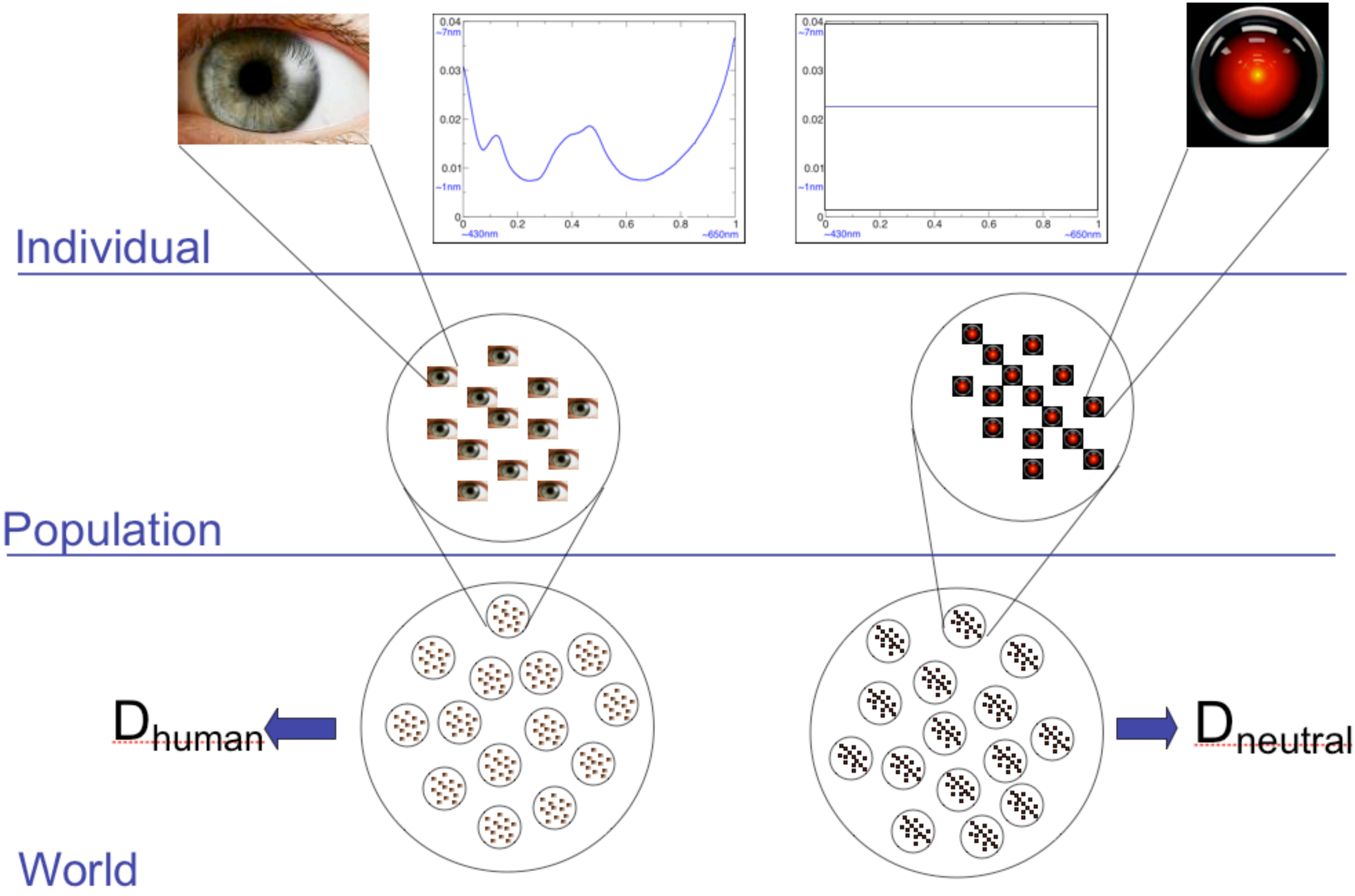
Paul Kay and Terry Regier
"Resolving the question of color naming universals"
Proc. Natl. Acad. Sci USA (PNAS) 100, 9085 (2003).

Human eyes discrimination ability d_{min}

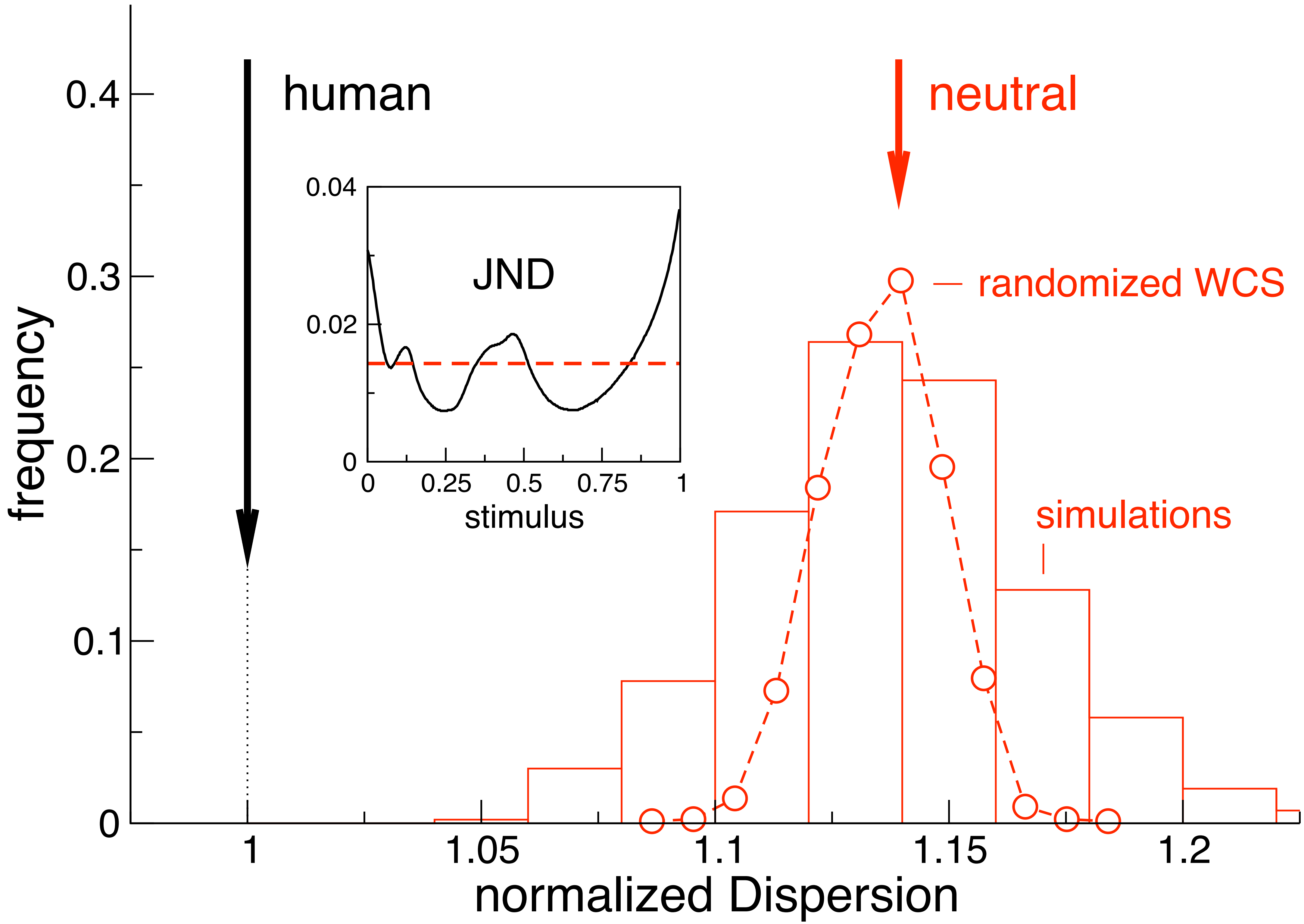


Long PH, Yang ZY, Purves D. 2006. Special statistics in natural scenes predict hue, saturation, and brightness. PNAS, 103(15): 6013-6018.

"In silico" version of the WCS



"In silico" version of the WCS



A. Baronchelli, T. Gong, A. Puglisi and VL,
Modeling the emergence of universality in color naming patterns
Proc. Natl. Acad. Sci. USA, 107, 2403 (2010).

An experimental avenue: the Web

human computing

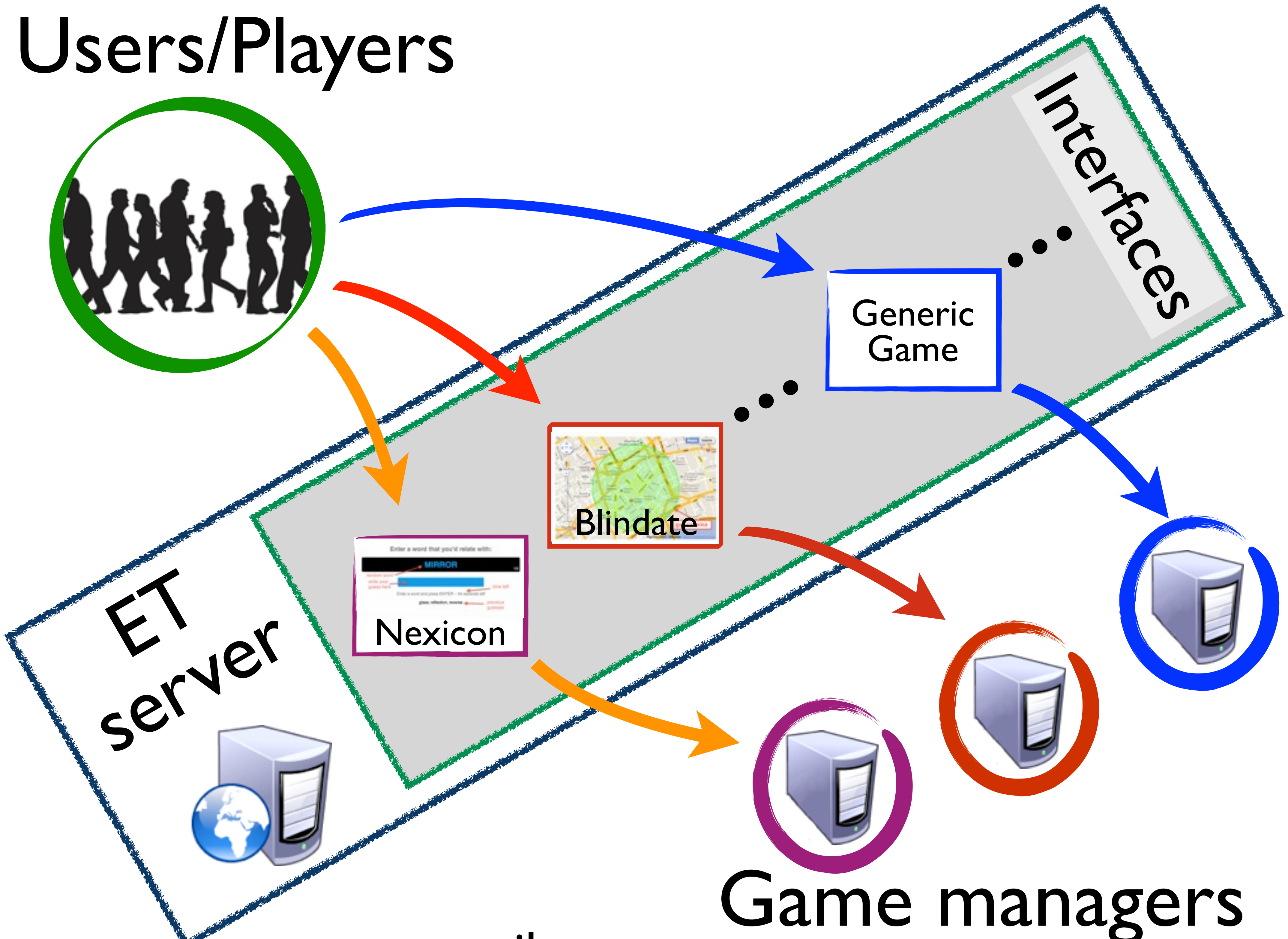
Populations of users facing collectively difficult problems using a small cognitive overhead

http://www.peekaboom.org/

- collaborative tagging
- online collaborative games
- collaborative filtering
- recommendation/trust networks

http://images.google.com/imagelabeler/

XTribe: a new web-based platform for web-gaming and social-computing



www.xtribe.eu

Post-doc positions open in Language Dynamics

DRUST: Digging for the Roots of Understanding

Post-doc position for 1+1 years

ISI Foundation - Turin

http://www.isi.it/

Post-doc position for 1+1 years

Recent publications

VL and L. Steels,
Emergence of Language
Nature Phys., Vol. 3, 758-760 (2007).

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Proc. Natl. Acad. Sci. USA, 105, 7936 (2008).

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Rev. Mod. Phys., 81, 591-645 (2009).

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A. Mukherjee, F. Tria, A. Baronchelli, A. Puglisi and VL,
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PLoS ONE, 6, e16677 (2011).

http://samarcanda.phys.uniroma1.it/vittorioloreto/

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