

# The Evolution of Lexical Usage Profiles in Social Networks

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# THE EVOLUTION OF LEXICAL USAGE PROFILES IN SOCIAL NETWORKS

## Background: The Problem of Lexical Change

- Lexical Change is typically messy (as opposed to grammaticalization):
  - influenced by changes in the world (technology, etc.)
  - influenced by  $\pm$ random events (“big” history, behavioral micropatterns, etc.)
- It is not always clear whether changes are about *meaning*, or about *prototypical usage patterns*.

### Example: French *voiture*

- 19<sup>th</sup> century and before: horse-drawn carriage
  - today: automobile, car
- The old meaning is still available today, even if it has become marginal.

- If random plays an important role, is it worth investigating?

What answer would the owner of a casino give you?

## Language and Social Networks

- Humans are an unusually social and cooperative species (for primates). As a consequence, all language learning (and most of language use) takes place in social networks.
- Network analysis is flourishing in the Social Sciences (see, e.g., Jackson, 2008), and is emerging in linguistics (see, e.g., Mühlendernd and Franke, 2012). A convergence is developing between game theory, social network analysis, and fairly old explanations developed by Hermann Paul in his *Prinzipien der Sprachgeschichte*.

Jede Veränderung des Sprachusus ist ein Produkt aus den spontanen Trieben der einzelnen Individuen einerseits und [...] Verkehrsverhältnissen andererseits. (Paul, 1995, §25)

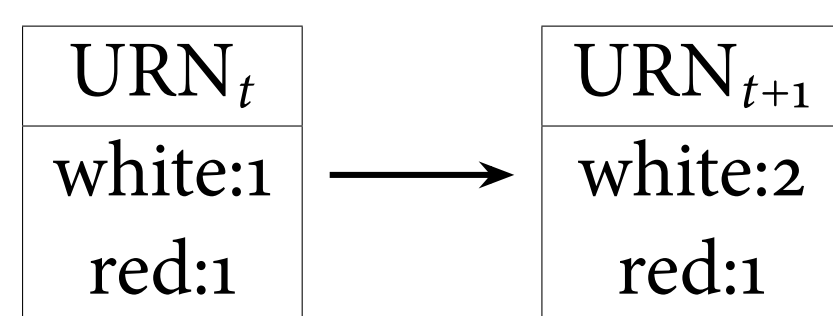
- Is (language) learning influenced by network size and structure? (**Yes!**, see, e.g., Mühlendernd and Franke, 2012)
- I will investigate reinforcement learning of (internally differentiated) lexical items in social networks, by performing multi-agent simulations.

## Reinforcement Learning with Polya Urns

### Learning in Behaviorism

Learning = shifting the probability of some behavior in an agent

- Polya-Urns provide a mathematical model of reinforcement learning.
- Randomly draw a ball from the urn.
- If the ball corresponds to the correct answer, a further ball will be added to the urn.



The probability of drawing “white” rises from 0.5 to 0.6

## Learning Internally Differentiated Lexical Items

- I assume internally differentiated lexical representations like Pustejovsky’s *qualia-structure*. The basic theoretical commitment boils down to independently ponderable submeanings.
- Motivation: meaning shifts generally follow patterns of polysemy
- Scenario:
  - We have two words that are absolute synonyms (see Skyrms, 2010): any draw = success
  - Each submeaning is an independent Polya urn (balls correspond to Word<sub>1</sub> & Word<sub>2</sub>)
  - Speaker draws a word, and signals to hearer
  - Hearer updates the weight for the chosen word (and maybe the speaker, too)

### Lexical Usage Profile of an Agent w.r.t. Denotation-Equivalents

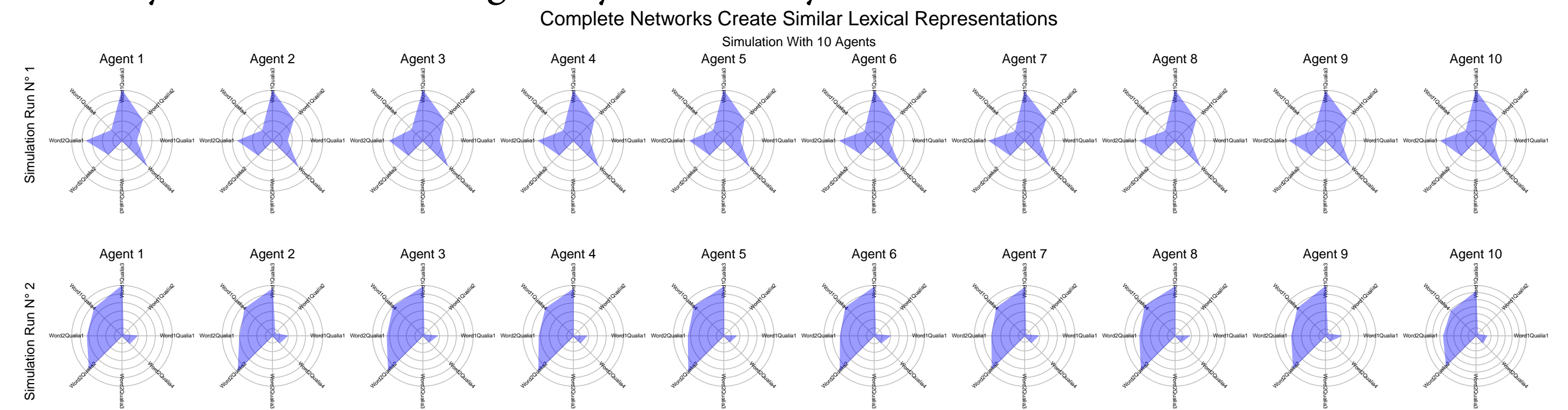
is represented as array of pondered submeanings with respect to these 2 words:

	W <sub>1</sub> Q <sub>1</sub>	W <sub>1</sub> Q <sub>2</sub>	W <sub>1</sub> Q <sub>3</sub>	W <sub>1</sub> Q <sub>4</sub>	W <sub>2</sub> Q <sub>1</sub>	W <sub>2</sub> Q <sub>2</sub>	W <sub>2</sub> Q <sub>3</sub>	W <sub>2</sub> Q <sub>4</sub>
Ag 1	1000	1000	1000	1000	1000	1000	1000	1000
Ag 2	2000	2000	2000	1	1	1	1	2000

Should we assume that a speaker reinforces (and therefore influences) himself? This has consequences for the outcome!

## Complete Networks: Contact Creates Uniformity

Within a simulation run in a complete network, the lexical usage profiles of the agents are extremely similar, even though they can be very dissimilar across simulation runs.

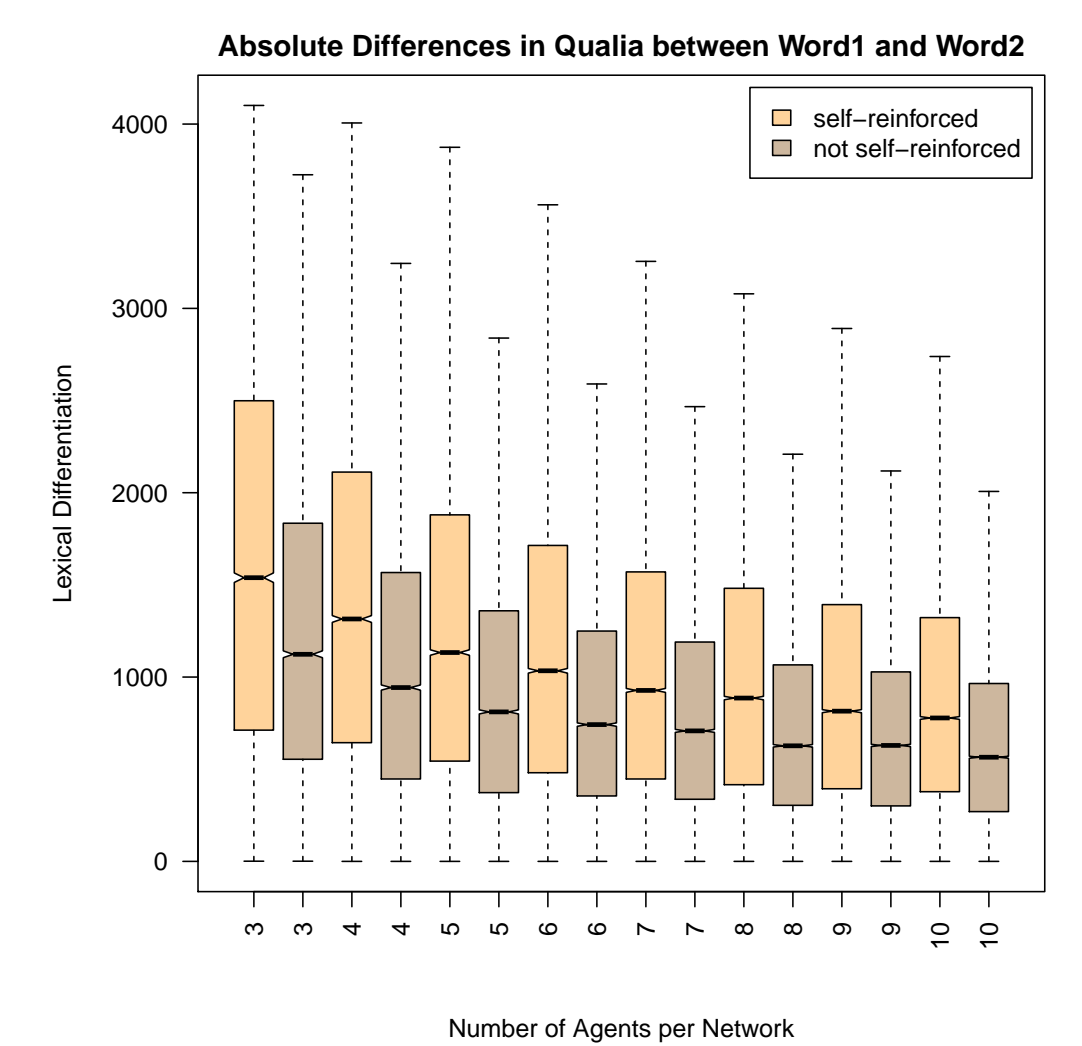


## Complete Networks: Lexical Differentiation and Network Size

**Definition: Lexical Differentiation between Word<sub>1</sub> and Word<sub>2</sub> at Submeaning<sub>i</sub>**

is the absolute difference of submeaning<sub>i</sub> of Word<sub>1</sub> and submeaning<sub>i</sub> of Word<sub>2</sub>, or:  
 $|\text{submeaning}_i(\text{Word}_1) - \text{submeaning}_i(\text{Word}_2)|$

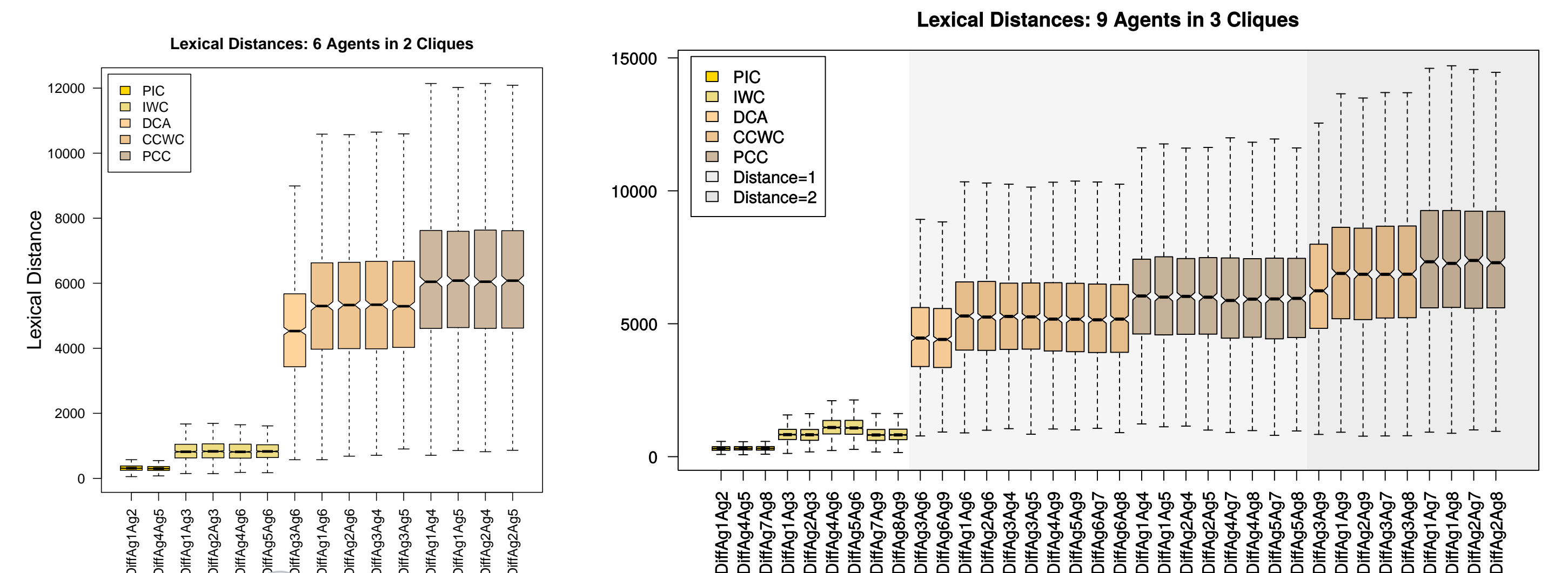
- In the simulation, we keep stable the number of reinforcements per agent.
- The bigger the (complete) network, the less differentiated the submeanings.
- If the speaker reinforces himself, differentiation is more important than if he does not reinforce himself.
- Differentiation strongly depends on the initial tendency. Self-reinforcement and small network size increase the chance of moving away from the initial configuration.



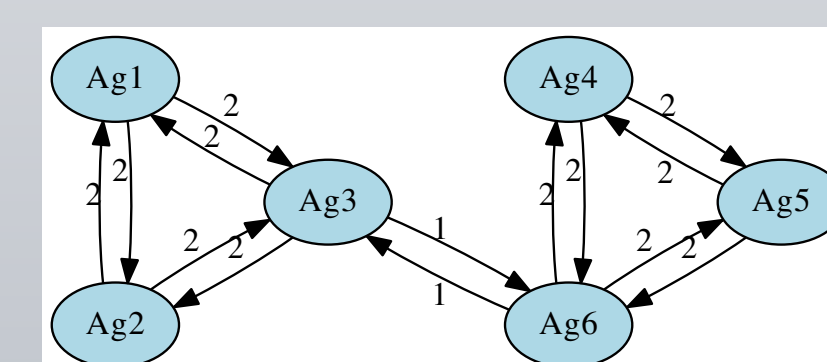
## Lexical Distance Reflects Network Structure

**Definition: Lexical Distance between Agent<sub>1</sub> and Agent<sub>2</sub>**

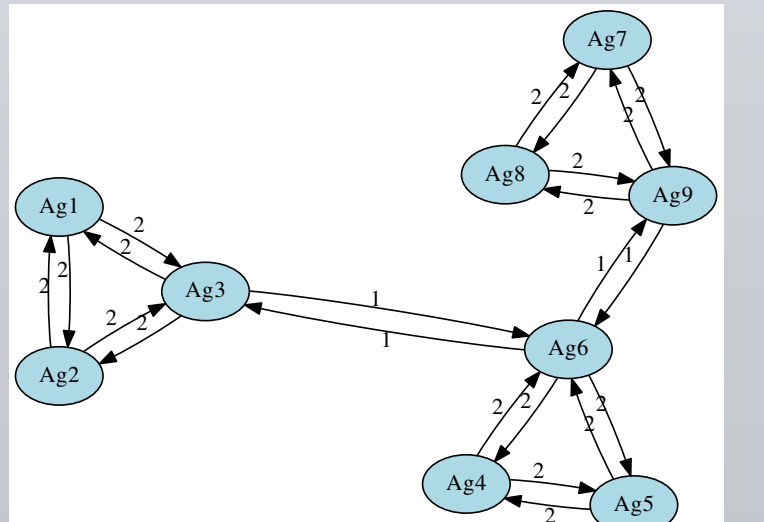
The lexical distance between two agents is the sum of the absolute differences of their respective pondered submeanings, or:  $\sum_{i=1}^k |\text{submeaning}_i(\text{Ag}_1) - \text{submeaning}_i(\text{Ag}_2)|$



Underlying Network:



Underlying Network:



## Acknowledgements & Sample References

I had the opportunity to present a previous version at the University Lille 3, and I would like the audience for their input. I would also like to thank Sylvain Billiard and Cédric Patin for their comments and encouragements. All errors and omissions are mine alone. All simulations have been performed with **sbcl** Common Lisp, using the **graph**-library by Eric Schulte (<https://github.com/eschulte/graph>). Networks have been drawn with **graphviz** (Gansner and North, 2000). Data analysis has been performed with **GNU R**.

[1] Gansner, E. R. and S. C. North (2000). “An Open Graph Visualization System and its Applications to Software Engineering”. In: *Software — Practice and Experience* 30.11: pp. 1203–1233. [2] Jackson, M. O. (2008). *Social and Economic Networks*. Princeton: Princeton University Press. [3] Mühlendernd, R. and M. Franke (2012). “Signaling Conventions: Who Learns What Where and When in a Social Network”. In: *The Evolution of Language: Proceedings of EvoLang*. Ed. by T. C. Scott-Phillips et al. Singapore: World Scientific: pp. 242–249. [4] Paul, H. (1995). *Prinzipien der Sprachgeschichte*. 9th ed. Tübingen: Niemeyer. [5] Pustejovsky, J. (1995). *The Generative Lexicon*. Cambridge: MIT Press. [6] Schaden, G. (2014). “Markedness, Frequency and Lexical Change in Unstable Environments”. In: *Proceedings of the Formal & Experimental Pragmatics Workshop*. Ed. by J. Degen, M. Franke, and N. Goodman. ESSLLI. Tübingen: pp. 43–50. [7] Skyrms, B. (2010). *Signals. Evolution, Learning, & Information*. Oxford: Oxford University Press.