The Evolution of Lexical Usage Profiles in Social Networks

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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 ±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*

- 19th 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 langage 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., Mühlenbernd 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 den […] Verkehrsverhältnissen andererseits. (Paul, 1995, §25)

- Is (language) learning influenced by network size and structure? (**Yes!**, see, e.g., Mühlenbernd and Franke, 2012)
- I will investigate reinforcement learning of (internally differenciated) 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.

URN_t		URN_{t+1}
white:1	$\longrightarrow$	white:2
red:1		red:1

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 Word1 & Word2)
  - 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

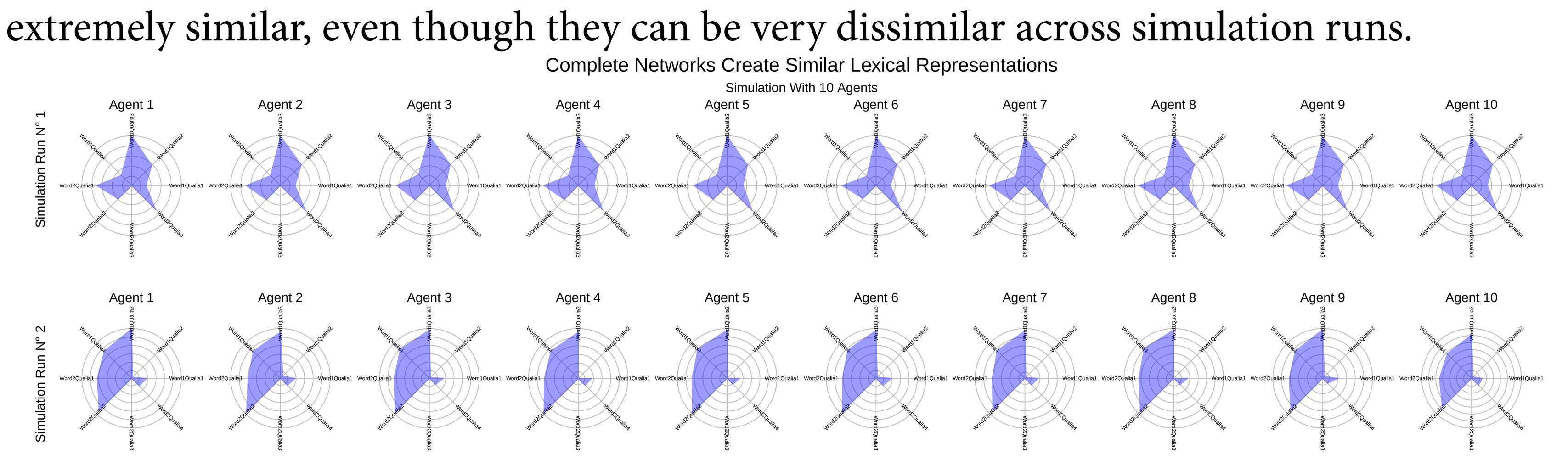
is represented as array of pondered submeanings with respect to these 2 words:

	W1Q1	W1Q2	W1Q3	W1Q4	W2Q1	W2Q2	W2Q3	W2Q4
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.

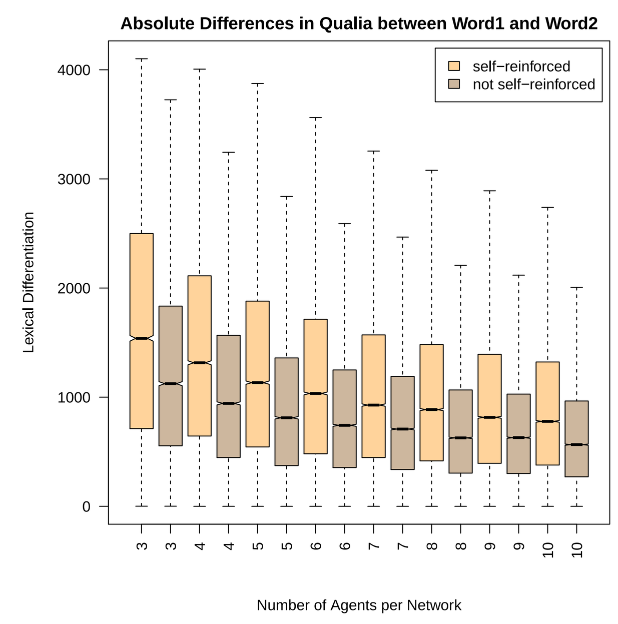


Complete Networks: Lexical Differentiation and Network Size

Definition: Lexical Differentiation between Word1 and Word2 at Submeaning$_i$

is the absolute difference of submeaning$_i$ of Word1 and submeaning$_i$ of Word2, or:
$|\text{submeaning}_i(\text{Word1}) - \text{submeaning}_i(\text{Word2})|$

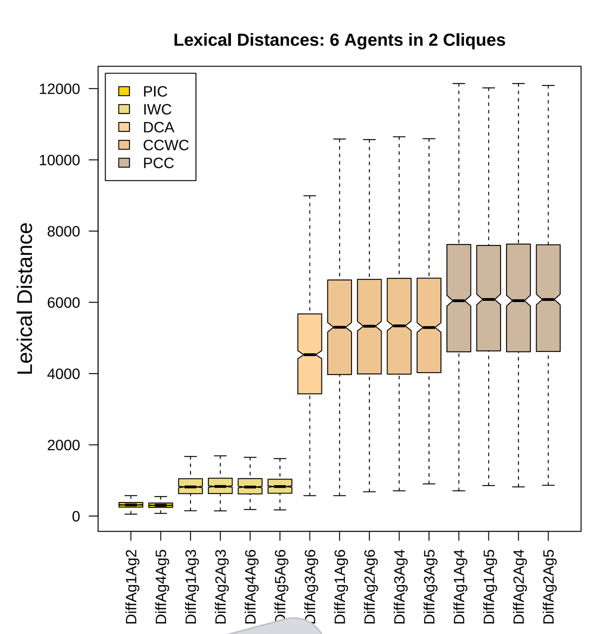
- In the simulation, we keep stable the number of reinforcements per agent.
- The bigger the (complete) network, the less differentiated the submeanings.
- If the speaker reinforces himself, differentiation is more important than if he does not reinforce himself.
- Differentiation strongly depends on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

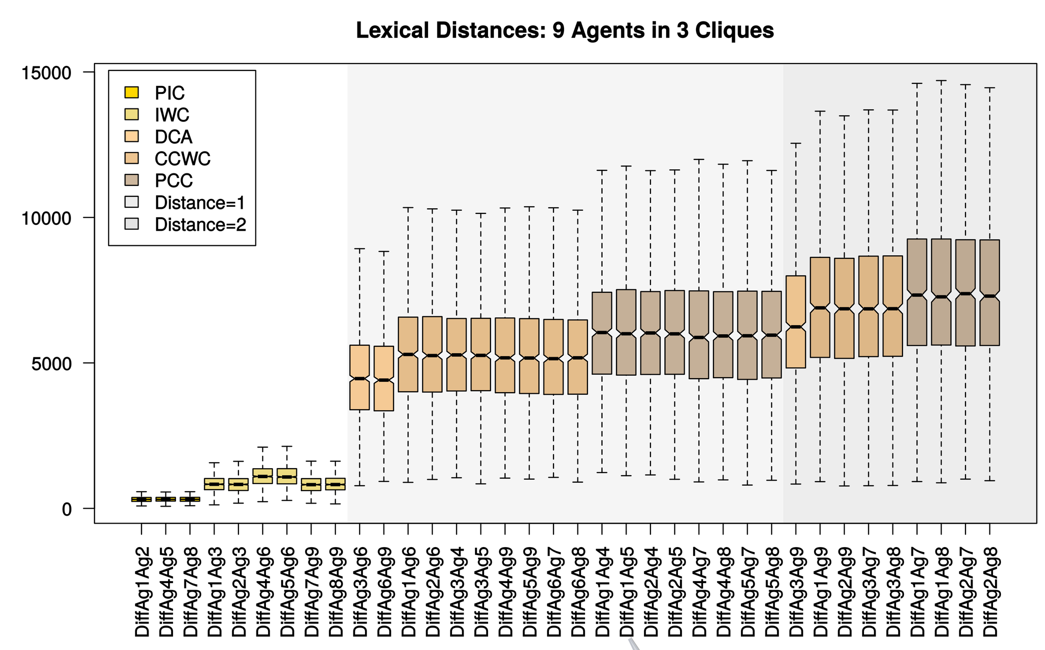


Lexical Distance Reflects Network Structure

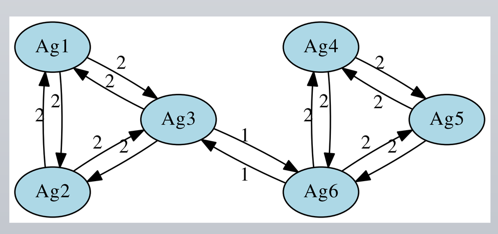
Definition: Lexical Distance between Agent1 and Agent2

The lexical distance between two agents is the sum of the absolute differences of their respective pondered submeanings, or: $\sum_{i=1}^{k} |\text{submeaning}_i(\text{Ag1}) - \text{submeaning}_i(\text{Ag2})|$

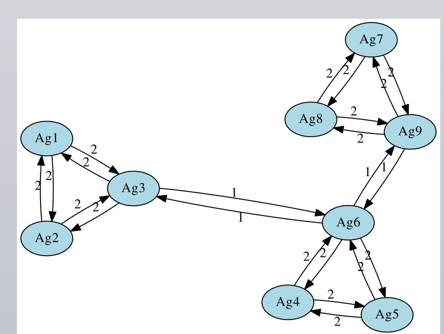




Underlying Network:



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**.

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