SIMULATING LANGUAGE CHANGE IN SOCIAL NETWORKS THROUGH DYNAMICS OF LEARNING AND INNOVATION

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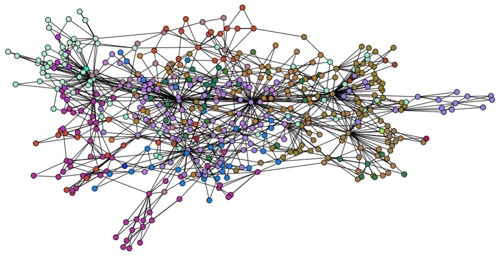
Introduction. In sociolinguistics, a prominent theory about the role of social network structure in language innovation is the 'weak tie'-theory (Milroy & Milroy, 1985): It states that a new variant i) typically emerges on so-called *weak ties*, and ii) spreads via *central members* of the language community. I deliver a synthetic approach to evaluating the 'weak tie'-theory: i) I present a computational model that incorporates game theory and network theory to simulate language change in artificial societies; ii) I analyze correlations between network features and behavioristic properties of agents in simulations. The results support the 'weak tie'-theory, presuming that tie strength is defined by neighborhood overlap.

Signaling Games & Social Networks. A number of computational studies have investigated language change in social network structures (cf. Ke, Gong, & Wang, 2008; Fagyal, Swarup, Escobar, Gasser, & Lakkaraju, 2010). Apparently, all these studies haven't modeled the concrete act of communication, but rather the very process of adopting one of several competing variants according to conditioning factors. To depict language use in a more fine-grained way, I apply a game-theoretic model: the signaling game (Lewis, 1969). The game models communication in form of an encoding-decoding process between a sender and a receiver. In my computational model agents are positioned in a scale-free small-world network structure (cf. Barabási & Albert, 1999) – constructed by the Holme-Kim algorithm (Holme & Kim, 2002) – and communicate with connected agents by repeatedly playing the signaling game, thereby switching between sender and receiver roles. An exemplary network of 500 agents is depicted in Fig. 1 (left).

Reinforcement Learning, Signaling Strategies & Innovation. By playing the signaling game repeatedly, agents update the cognitive disposition that governs communicative behavior. To keep the model simple, I used a simple learning rule: Roth-Erev reinforcement learning (Roth & Erev, 1995). In this way agents incrementally adopt a communicative strategy that – in the optimal case – evolves to a so-called *signaling system*: a pair of sender and receiver strategy that i) forms a one-to-one mapping between meanings and forms, and ii) ensures perfect communication (Lewis, 1969). The given learning model is extended by an innovation



	INV	IMP
DC	-.06	**.74**
CC	.03	**.35**
BC	-.01	**.70**
TS	**-.38**	-.18

Figure 1. **Left:** A small-world network structure with 500 nodes (= agents), segmented in different regions of *local signaling systems*. **Right:** Pearson correlation values between agents' i) network features DC, BC, CC and TS, and ii) dynamic behavioristic properties INV and IMP.

mechanism that allows agents to create new forms (cf. Skyrms, 2010; Alexander, Skyrms, & Zabell, 2012). It can be shown that this extended learning model enables two things: i) the emergence of regions of local signaling systems in a social network (Wagner, 2009), as depicted in Fig. 1 (left), and ii) the change of those regions over time, induced by the innovation mechanisms (Mühlenbernd, 2014).

Experiments. To simulate language change, I used a computational model of 500 agents that i) are positioned in a scale-free small-world network, ii) communicate repeatedly with connected agents by playing the signaling game, and iii) update their cognitive disposition by innovative reinforcement learning. I conducted 10 simulation runs over 10,000 simulation steps (each agent plays with each neighbor in each communication step). In each simulation run around 10 different regions of local signaling systems emerged (cf. Fig. 1 (left)) and changed over time. To test the 'weak tie'-theory, namely that innovation i) emerges on weak ties, and ii) spreads via central nodes, I measured the network features for centrality and connectivity of each agent and contrasts them with behavioristic characteristics of agents concerning their role in the process of change. To be more concrete, as network features I measured *degree centrality* (DC), *betweenness centrality* (BC) and *closeness centrality* (CC) (cf. Jackson, 2008), and a value for *tie strength* (TS) that defined an agent's average strength of ties according to her neighborhood overlap (cf. Mühlenbernd, 2014). To analyze behavioristic characteristics of agents that depict their role in language change I measured the following two dynamic properties: i) *inventiveness* (INV): the number of times an agent switched to a new strategy not used by any other agent in the population; ii) *impact* (IMP): the number of times an agent's strategy was adopted by a neighboring agent.

Results. The Pearson correlations of all 5,000 data points (10 runs with 500 agents each) between network features and dynamic properties support the 'weak tie'-theory: i) a non-trivial negative correlation between TS and INV, indicating that innovation is reinforced through weak ties; and ii) a non-trivial positive correlation between IMP and all centrality values, showing that centrality supports the spread of (new) variants (Fig. 1, right).

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