

Language Change and Network Games

Abstract

Studies of language change and variation in sociolinguistics investigate the correlations between social variables and phenomena like vernacular speech norms, code switching, and dialect continua. In multiple studies, researchers claim one variable as i) particularly decisive and correlative for a number of phenomena, and ii) almost universally applicable: the social network structure (Milroy 1980). This article summarizes previous work incorporating network theory in questions of language change and discusses a practice noticeably absent from classical sociolinguistics: the simulation of language change. In simulation experiments, sociolinguistic theories of language change – especially those employing social network structure – can be tested in a virtual society free from the hindrance of data sparseness. In this context, the model of game theory can be utilized to construct individuals' interaction for more robust and feasible results.

1 Introduction

Two dominant issues in sociolinguistics are language change and variation. A significant amount of sociolinguistic research investigates how social variables affect linguistic usage over time and space. In particular, linguistic behavior can vary between groups differentiated along lines like status, gender, ethnicity, or education. Of these properties, it has been noted that the structure of a person's social network (links to family members, colleagues, friends, etc.) might be crucially important for explaining language variation and change (c.f. Labov 2001, Eckert 2005, L. Milroy and Llamas 2013), particularly because of its universal character, a quality that other social features generally lack. Since the early 1980s, the social network approach (L. Milroy 1980) has been used in various field studies. Their results document social network structure as a

27 robust and impartial predictor of language change.

28 Since the late 1990s, a number of studies have emerged that analyze lan-
29 guage change in a more universal sense – abstracted away from the specifics
30 of usage – by conducting ‘virtual field work’ in computer simulations (Nettle
31 1999, Ke, Gong and Wang 2008, Fagyal et al. 2010). With a computer program
32 simulating and documenting a virtual linguistic community, many of the possi-
33 ble shortcomings of network approaches in fieldwork – like a sparse coverage of
34 essential data in time and space – can be overcome. As a virtual society gives
35 full access to spatial and temporal data, network properties can be defined and
36 observed in a very fine-grained way. Admittedly, virtual computer programs
37 cannot reproduce speech communities in every detail, but we claim they are a
38 valuable tool for both reproducing field studies and reassessing the subsequent
39 theoretical developments.

40 Despite their upside, most of the previously mentioned simulation studies do
41 not include an essential aspect of simulating language change: the actual act of
42 communication (in terms of a speech production and perception process). Thus
43 we argue for a more fine-grained and realistic approach, incorporating game-
44 theoretic techniques that model how speakers and hearers arrive at linguistic
45 conventions. To get a fair impression of how such a combination can be applied
46 to test theories of language change, we will present an exemplar for a virtual
47 study at the end of this article.

48 The article is structured as follows: Section 2 gives a short introduction to
49 the social network approach in sociolinguistics. Section 3 introduces a noted
50 social network theory related to language change, called the ‘weak tie’-theory
51 (J. Milroy and L. Milroy 1985). Section 4 discusses the obstacles that bedevil
52 sociolinguistic theories like the ‘weak tie’-theory from being directly verified
53 in field research. Section 5 points out alternatives for evaluating theories of

54 language change, inter alia simulation studies, which are discussed in Section
55 6 in more detail. Section 7 presents and advocates for game-theoretic mod-
56 els of language change. Section 8 presents a sample study that integrates a
57 game-theoretic model towards examining the ‘weak tie’-theory. Finally, Sec-
58 tion 9 points out further theories of language change that may be amenable to
59 computational models.

60 **2 Networks in Sociolinguistics**

61 Early field studies recognized that social variables like status, gender, ethnicity
62 or the level of education cannot give a universal explanation for linguistic diver-
63 sity (c.f. Labov 1963, 1966, 1972, J. Milroy and L. Milroy 1978, Eckert 1989). In
64 contrast, the ‘social structure’ of the community seems to be a source of variation
65 that might be highly independent of environmental circumstances and universal
66 in character.¹ In an early study, James Milroy and Lesley Milroy (1978) found
67 a positive and significant relationship between so-called network scores and the
68 use of vernacular language in different communities in Belfast. This led to a
69 number of subsequent works illustrating the practice of social network analysis
70 in sociolinguistics (c.f. L. Milroy 1980, J. Milroy 1990 and Chambers 1995).

71 In questions of language diversity, such as the emergence and coexistence of
72 different socio- and dialects of the same language, some properties of network
73 structure seem to be particularly important. One significant distinction is that
74 of a ‘close-knit’ and a ‘loose-knit’ network. In a pioneering work – by being
75 a systematic account of articulating network structure – Lesley Milroy (1980)
76 defines a close-knit network as one that has a high ‘density’ and mostly ‘strong
77 ties’. Here density referring to the ratio of ties and members of a community,
78 and strong ties are defined as incorporating multiple relationships between two
79 members, such as kin relationship, friendship or work fellow. In close-knit net-

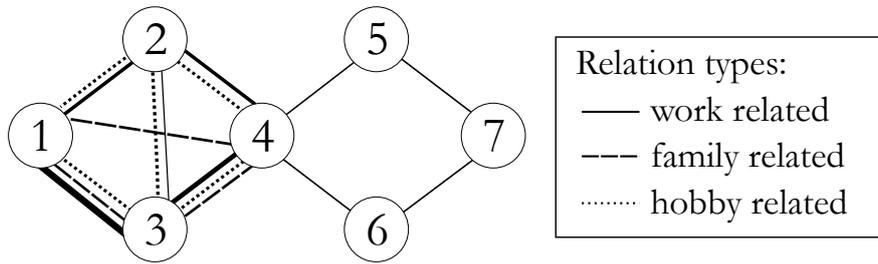


Figure 1: The subnetwork containing 1, 2, 3 and 4 represents a typical close-knit network: i) all members know each other (there is at least one tie between any two members), thus the network has maximal density, ii) almost all members have multiplex ties (except of member 1 and 4, all members are connected via more than one relation type), and iii) all members have frequent contact (the thickness of a tie represents the frequency of interaction). Conversely, the subnetwork containing 4, 5, 6 and 7 represents a typical loose-knit network: i) not all members know each other directly (4 and 7, 5 and 6), ii) all connections are uniplex (only work related), and iii) the members have a low frequency of interaction (represented as thin ties).

80 works it is expected that all members

81 i) mostly know each other,

82 ii) interact frequently with each other inside a defined area,

83 iii) have a great volume of exchange and shared knowledge, and

84 iv) are susceptible to the obligation to adopt group norms.

85 In contrast, a loose-knit network is a structure with a low density and mostly
 86 ‘weak ties’, thus single-type relationships. Members of such a structure are
 87 attested to have an open personal network and no particular linguistic markers
 88 of identity (c.f. Fried and Fitzgerald 1973) or a high degree of dialect diffuseness
 89 (c.f. Le Page and Tabouret-Keller 1985). Figure 1 illustrates the structural
 90 differences between a close-knit and a loose-knit network.

91 We introduce network features like *close-knit* and *loose-knit* as exemplary
 92 sociolinguistic factors to yield the following point: the network structure of a lan-

93 guage community has two properties that are suitable for developing more gen-
94 eral theories of language variation and change: i) a universal character (c.f. Mil-
95 roy 1980, see endnote 1) and ii) an obvious correlation with linguistic behavior.
96 This leads us to discussing the role of network structure in language change.

97 **3 The Role of Network Structure in Language** 98 **Change**

99 In its most general sense, language change can be seen as a new linguistic variant
100 replacing an old one across some set of contexts. Although each instance of
101 linguistic change has its temporal and spatial inception, one of the greatest
102 challenges in sociolinguistics is determining which social variables support the
103 initiation and propagation of a new variant (c.f. Labov, Yaeger and Steiner
104 1972, Trudgill 1972, Labov 1973, 2001, 2010, L. Milroy 1980, Rogers 1995, Croft
105 2000, Chambers 2002). To better understand language change, we should ask:
106 Which social circumstances support linguistic innovation? And which social
107 environment is a fertile ground for a new variant to spread?

108 An insightful theory about the role of ‘social network structure’ in language
109 change is the ‘weak tie’-theory (J. Milroy and L. Milroy 1985)². As a result of
110 speaker innovation, a new variant i) emerges generally on so-called ‘weak ties’
111 – ties that have a low strength or multiplexity and connect mostly detached
112 communities (see Figure 2) – and ii) spreads via ‘central’ members of the local
113 community. A number of studies indirectly support the ‘weak tie’-theory (Labov
114 1973, 1991, 2001, Trudgill 1988, L. Milroy and J. Milroy 1992, J. Milroy 1996,
115 Wolfram and Schilling-Estes 1998, Llamas 2000, L. Milroy and Gordon 2003),
116 but studies that directly verify the theory are hard to conduct, for reasons that
117 we will soon delineate.

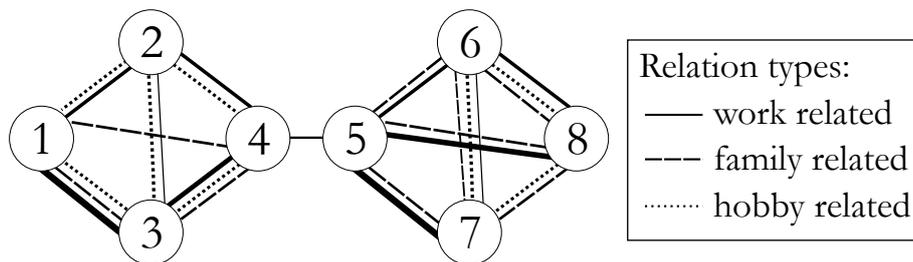


Figure 2: The connection between member 4 and 5 constitutes a typical weak tie: it i) has a low strength/frequency (thin line), ii) has minimal multiplexity (uniplex), and iii) connects two detached communities, here community A (members 1, 2, 3, 4) and B (members 5, 6, 7, 8). According to the ‘weak tie’-theory, innovation emerges on such weak ties and spreads via central members of a community like A or B.

118 4 The Quantity Problem of Empirical Studies

119 A systematic analysis of the impact of a linguistic community’s network struc-
 120 ture on language change involves the calculation of network features of particular
 121 members of that community. As we will delineate later, an important role in
 122 language change is assigned to so-called ‘global features’, that are network prop-
 123 erties with respect to a ‘global environment’, a part of the network that goes
 124 far beyond the local neighborhood of this member. The calculation of such fea-
 125 tures needs a quantity of network data that generally field work studies cannot
 126 deliver. This obstacle leads to a practice in field work of generally considering
 127 first-order networks, as explained by L. Milroy and Llamas (2013:411):

128 “A social network may be seen as a boundless web of ties which
 129 reaches out through a whole society, linking people to one another,
 130 however remotely. [...] However, sociolinguistic research has gen-
 131 erally focused on face-to-face interaction, and usually on first-order
 132 network ties – that is, those persons with whom an individual di-
 133 rectly interacts.”

134 Gathering data on first-order networks can suffice for analyzing individual-
135 based theories of norm maintenance in close-knit networks, but this fails to
136 predict phenomena that might be correlated to more global networks values,
137 like cluster-related features. L. Milroy and Gordon (2003:119) point out:

138 “Network analysis [in sociolinguistics] typically deals with the struc-
139 tural and content properties of the ties that constitute egocentric
140 personal networks, and seeks to identify ties important to an indi-
141 vidual rather than to focus on particular network clusters (such as
142 those contracted at school) independently of a particular individual.”

143 All in all, we can see the difficulty of gathering a critical mass of data needed
144 to compare individuals in loose-knit structures in a meaningful way.

145 Related to the quantity problem is the difficulty of obtaining temporal data.
146 To record language change, it is often not enough to compare different age groups
147 – see e.g. ‘apparent-time construct’ (c.f. Bailey 2002). Rather it might be neces-
148 sary to conduct expensive and arduous longitudinal or cohort studies (c.f. Dan-
149 nenberg 2000), which are comparatively rare in sociolinguistics (c.f. Cukor-Avila
150 and Bailey 1995, Blake and Josey 2003). Delving deeper into this discussion ex-
151 ceeds the scope of this article, but the point remains. In the next section we
152 want to recommend alternatives for surmounting the shortcomings of the afore-
153 mentioned network analysis in sociolinguistics.

154 5 Alternative Methods in Sociolinguistics

155 One consequence of the quantity problem is that feasible computations of global
156 network properties that illuminate the larger picture of a speech community
157 require methods like mining ‘communities of practice’ (Wenger 1998, Eckert
158 2005). As a prominent example, in her studies of Detroit schools, Eckert (1989)

159 recorded complete friendship networks, hypothesizing that particular groups or-
160 ganize in specific structures and contain themselves to specific speech norms.
161 Although her uptake is suitable for computing globally-related network proper-
162 ties, the reader should nevertheless note that such a network is only a fragment
163 of the members' network ties, since it considers exclusively the participants of
164 a particular community of practice (e.g. classmates, work fellows, etc.), and is
165 therefore uniplex and incomplete.

166 A more precise picture of a social network structure can be provided by
167 the study of online chat networks (e.g. Paolillo 2001, Merchant 2001). These,
168 for example, allow us to measure the 'intensity tie strength' quite precisely by
169 measuring the amount of time two members spend chatting together. There are
170 crucial drawbacks to such studies however. For one, note that a chat commu-
171 nity can be seen as an 'online community of practice' (Wenger, White and Smith
172 2009). Furthermore, it is debatable to what degree these results are contribu-
173 tions to questions of language change in the classical sense, since chat via text
174 differs in a number of aspects from verbal communication (for a discussion about
175 similarities and dissimilarities, and the role of written text in sociolinguistics,
176 we refer to Baron 2000, 2008, and Crystal 2005).

177 A further possibility then is to leave the terrain of field work entirely by
178 doing simulations with virtual societies. In light of the quantity problem, the
179 advantages are clear: first, the researcher creating the whole society has ac-
180 cess to the full network structure. It is thus possible to compute the relevant
181 global network properties with absolute precision. Second, it is also possible
182 to record an individual's behavior with full recall. Third, simulations generally
183 run quickly, so interaction over time can be computed in a feasible time frame,
184 thus overcoming the difficulty of longitudinal studies.

185 The obvious drawback of such virtual experiments is the abstraction from

186 real human behavior. However, as virtual experiments test theories of language
187 change originating from field research, they can remain ‘informed’ by real human
188 behavior. It should furthermore be noted that in research areas with a much
189 greater quantity problem, e.g. ‘language evolution’, simulation studies are an
190 established modus operandi for conducting research (c.f. Nowak and Krakauer
191 1999, Cangelosi and Parisi 2002, Kirby and Hurford 2002, Steels 2002). In
192 the following section, we will introduce and discuss network simulation studies,
193 presenting along the way some noteworthy work on language change.

194 **6 Network Simulation Studies of Language Change**

195 What constitutes a network simulation study? First, the ‘simulation’ aspect sig-
196 nifies that we are studying a virtual system, in our case a system of agents using
197 artificial language. For that purpose, i) we create and implement a computer-
198 based model of interacting agents , ii) we initialize multiple runs, possibly un-
199 der different initial conditions (parameters), and iii) we analyze the output of
200 the system. Such an approach tests different theories by integrating theory-
201 driven assumptions and comparing the output of the runs with empirical data.
202 We claim this ‘synthetic approach’ is an excellent supplement to formal theo-
203 ries about dynamic social systems, especially when real-world data is restricted
204 and/or fragmentary (c.f. the quantity problem).

205 The ‘network’ aspect signifies that the interactions are structured according
206 to the varying connections between members in the system.³ By incorporating
207 a heterogeneous social network structure, we add realism and more robust pre-
208 dictive power. As agents differ in connective properties, e.g. the number of ties
209 to other agents or the centrality of their position in the network. This allows us
210 to detect the impact of network-specific properties on their behavioral patterns.

211 Note that while a number of simulation studies of language change and

212 contact have emerged in the last 20 years (c.f. Clark and Roberts 1993, Briscoe
213 2000, Hurford 2000, Yang 2000, Niyogi 2002, Abrams and Strogatz 2003, Schulze
214 and Stauffer 2006), many of them do not consider network structure. In contrast,
215 there are three noteworthy articles that we want to discuss, exemplifying how a
216 network simulation study can be done (Nettle 1999, Ke et al. 2008, and Fagyal
217 et al. 2010).

218 Nettle's (1999) approach simulated the interactive behavior of members em-
219 bedded in a grid structure, where spatial distance represents social distance and
220 each agent can only possess one of two competing variants of a linguistic item.⁴
221 In each step of a simulation run, each agent can keep her current variant or can
222 adopt the other one based on which one has the higher 'impact' value. This
223 impact value is a combination of i) a social impact value that integrates the
224 number, social status and social distance of other members using this variant⁵,
225 and ii) a functional bias of the variant. Nettle tested his system for a range of
226 different parameter settings and came to the following results: i) a full substi-
227 tution of one variant over the other can only take place when super-influential
228 high-status agents are involved, and ii) a functional bias alone is never enough
229 for a new variant to replace the old one; there is always a high social impact
230 value required.

231 Ke et al. (2008) criticize Nettle's study on two points: i) they regard Nettle's
232 regular spatial network structure as unrealistic, and ii) they stress that Nettle's
233 results fail to explain a phenomenon which Labov (2001) calls 'changes from
234 below': linguistic change that has emerged in lower social classes, and not only
235 by super-influential, high-status agents. Thus, Ke et al. adopt a light version of
236 Nettle's impact equation, but integrate it in a model of more realistic social net-
237 work structures: so-called 'small-world networks'⁶ (Watts and Strogatz 1998).
238 Their results reveal that a new variant can replace an old one even without

239 super-influential agents, but it must have an enormously high functional bias in
240 comparison to its competitor. In sum, both Nettle (1999) and Ke et al. (2008)
241 used network simulation models to investigate the propagation of a new variant,
242 but both also integrated a functional bias – a network independent value – that
243 plays an important role in their analyses.

244 The following simulation study can be considered as ‘state of the art’ in
245 network simulation studies investigating language change: Fagyal et al. (2010)
246 use ‘scale-free’⁷ small-world networks with directed ties denoting the direction
247 of influence, considering eight different competing variants. Members of the
248 network i) have a status value proportional to their outgoing ties, ii) adopt a
249 new variant of a neighbor (connected member) with a probability proportional to
250 the neighbor’s status, and iii) have only one variant at a time in their inventory.
251 Note that Fagyal et al. – in contrast to Nettle and Ke et al. – i) do not consider
252 any functional bias, and focus on the impact of social biases in terms of status,
253 and ii) define status only in terms of network structural features (outgoing ties).
254 This point advances the social network approach by explaining language change
255 in terms of network properties, and Fagyal et al. follow this direction by taking
256 such properties into consideration exclusively.

257 Their results show first that the propagation of a variant is realized by
258 ‘central influential’ members⁸, something in accordance with Nettle’s result of
259 super-influential agents being a necessary condition for society-wide spread of a
260 variant. As a second result, they show that ‘peripheral low-connected’ members
261 – so-called loners – are the source for innovations. The results of Fagyal et
262 al. therefore support the ‘weak tie’-theory to some degree, although they don’t
263 show directly that innovation emerges on weak ties. Instead, they show that
264 innovation starts with loners, who are by definition not (strongly) embedded in
265 a dense local structure. These agents are therefore expected to have weak rather

266 than strong ties. Furthermore, they show that innovation spreads via central
267 members, according with the ‘weak tie’-theory. This study therefore exemplifies
268 a sociolinguistic application of network simulation studies.

269 In summary, a network simulation study investigating language change can
270 be conducted as follows: take a social network structure, where the nodes rep-
271 resent individuals (agents) and the ties are possible channels of influence or
272 communication. Next, give each agent an inventory of variants of linguistic
273 items. Then, update this inventory after each step of a simulation run depend-
274 ing on the impact of the variant. This impact can depend on various factors
275 and therefore be defined in multiple ways, along with the design of the network
276 structure, as outlined through the stated noteworthy studies.

277 Note that these studies have one thing in common: they depict individual
278 language change simply as the mechanism of one linguistic variant replacing
279 another one. Therefore they exclude an essential feature of language: ‘commu-
280 nicating’ information from a speaker to a hearer (see Mühlenbernd and Quinley
281 2013). In the next section, we argue for a more concrete design through game-
282 theoretic modeling: the ‘signaling game’.

283 **7 Game Theory and Language Change**

284 Only recently have game-theoretic studies featured in sociolinguistics (c.f. Müh-
285 lenbernd and Franke 2012, Dror et al. 2013, Ahern 2014). Broadly put, game
286 theory is a branch of applied mathematics concerned with group interaction
287 and decision-making. Game theory’s notions of rationality, expected utility,
288 evolutionary stability, and equilibrium have provided a mathematical founda-
289 tion for understanding how linguistic conventions can emerge and stabilize in
290 a population through the interaction of rational actors. In the last 25 years,
291 ‘game-theoretic linguistics’ has grown as a field, but it has mainly concerned

292 itself with two subdomains: language evolution and pragmatics (c.f. Jäger 2008,
293 Benz et al. 2011). As an exception, Quinley and Mühlenbernd (2012) used
294 game-theoretic models to simulate a historic case of language contact and dif-
295 fusion. In a review article (Mühlenbernd and Quinley 2013:129) they argue:

296 “[...]when we want to analyze language use in a more concrete way in
297 terms of how it happens, namely by considering the communicative
298 act itself, game-theoretic methods have appeal as a recently well-
299 vetted techniques to model communication.”

300 Many studies in game-theoretic linguistics have implemented the signaling
301 game (Lewis 1969) as a model of communication between a speaker and a hearer.
302 This model depicts an encoding-decoding process, interpreting linguistic conven-
303 tions as stable systems from which no rational actor would deviate. As speakers
304 choose variants of messages corresponding to their own private information and
305 hearers choose interpretation of those messages, the meaning of each variant
306 emerges as a correspondence between information and interpretation.

307 The versatility of signaling games in linguistics is documented by a diverse
308 set of applications, e.g. the emergence of semantic meaning in homogeneous pop-
309 ulations (Skyrms 1996, Huttegger and Zollman 2011) or in network structures
310 (Zollman 2005, Wagner 2009), the rational basis of pragmatic enrichment like
311 implicatures (Jäger 2007a, van Rooij 2008, Franke 2009), and the evolutionarily
312 stable aspects of case marking (Jäger 2007b) and vowel systems (Jäger 2008).
313 In particular, the utility of signaling games in i) pragmatics on one hand, and
314 ii) language evolution and stability on the other lead us to the claim that ap-
315 plying signaling games for studying language change and variation is a natural
316 progression (Mühlenbernd 2014). To get a good impression of how signaling
317 games can contribute to understanding sociolinguistic phenomena, we refer to
318 Mühlenbernd and Quinley (2013).

319 Let us elaborate on network simulations with game-theoretic communication
320 models like signaling game. First recall the network simulation model introduced
321 in Section 6, based on the exemplary studies presented there: here an agent
322 adopts a new variant by the virtue of its impact on her. If we model linguistic
323 variants as cultural items that spread in dependence of their functional or social
324 bias, this does not dissociate them from the general propagation process of any
325 other cultural item like opinions, trends or non-linguistic conventions. Modeling
326 the adoption and propagation process of a variant of a ‘language item’ therefore
327 requires a model of communication between a speaker and a hearer, since it is
328 the success of the communicative act that drives a hearer to adopt a variant
329 and a speaker to propagate it.

330 Thus, our game-theoretic network simulation model involves communication
331 – via a signaling game – between agents in a network. Since we want to model
332 an adoption process, agents play this game repeatedly and get feedback about
333 the result of the game, thus ‘learning’ the convention based on this feedback.
334 At this point, the designer has to make an additional choice: how do agents
335 update the feedback information? Here, a number of different ‘update rules’
336 have proven themselves as good candidates for models of learning and revising
337 previous information (see c.f. Huttegger and Zollman 2011 for an overview).

338 It is important to note that many signaling game studies have demonstrated
339 how a particular linguistic convention or behavior emerges, but not how it
340 changes.⁹ There are two such studies that apply signaling games in network
341 simulation models for questions of language change (Mühlenbernd and Nick
342 2013, Mühlenbernd 2014). In these studies the update rule of the signaling
343 game is equipped with an innovation mechanism that allows agents to create
344 new forms based on the success of the actual forms in usage. This leads to the
345 result that linguistic behavior does not necessarily stabilize, but rather persists

346 in continuous change. Mühlenbernd and Nick (2014) used this model on a spa-
347 tial network structure to simulate the emergence and alteration of regions of
348 local conventions, whose outcome resembled a ‘dialect continuum’. In addition,
349 Mühlenbernd (2014) used this model on a scale-free small-world network struc-
350 ture and analyzed the sources of innovation and propagation, according with the
351 results of Fagyal et al. (2010) and the ‘weak tie’-theory by J. Milroy and L. Mil-
352 roy (1985), namely that the sources of innovation are peripheral agents with
353 mostly weak ties, whereas agents in central positions are the most influential
354 ones and therefore instigators of propagation.

355 To give an impression of how a network simulation model integrated with
356 a signaling game might appear in detail, we will next consider an exemplar for
357 such a study, investigating components of the ‘weak tie’-theory.

358 **8 A Simulation Experiment for Reassessing the** 359 **‘Weak Tie’-Theory**

360 With the following study, we want to exemplify how a computational model can
361 aid the examination of sociolinguistic theories by reassessing particular aspects
362 of the ‘weak tie’-theory as introduced in Section 3. Recall that one important
363 network property of the ‘weak tie’-theory is the ‘strength of a tie’. To analyze
364 this property in a formal, computationally tractable way, it is necessary to give
365 a precise, network-theoretic definition. Unfortunately, it is not clear from the
366 literature exactly how these properties are defined.

367 According to her pioneering work, Lesley Milroy (1980) considers a tie as
368 weak, if it realizes a relationship of a low degree of multiplexity. In defining
369 the ‘weak tie’-theory J. Milroy and L. Milroy (1985) build on a definition given
370 by Granovetter (1973:1361): “the strength of a tie is a (probably linear) com-

371 bination of the amount of time, the emotional intensity, the intimacy (mutual
372 confiding) and the reciprocal services which characterize a tie.” J. Milroy and
373 L. Milroy remark that this definition fits roughly with the assumption of defin-
374 ing tie strength by the degree of multiplexity. In accordance with this position,
375 we denote this definition of tie strength as ‘Intensity Tie Strength’ (*ITS*).

376 However, there are further characteristics of tie strength in the original the-
377 ory. J. Milroy and L. Milroy also align with Granovetter in the following hy-
378 pothesis: the stronger the tie between two members, the larger the proportion of
379 common members to whom both are tied. This proportion is also known as the
380 ‘neighborhood overlap’. Easley and Kleinberg (2010, Chapter 3) point out that
381 the value of neighborhood overlap is increasing with an increasing *ITS* value.
382 Granovetter’s hypothesis and the indication by Easley and Kleinberg both cor-
383 respond to the assumption that strong ties are found in structures where a high
384 neighborhood overlap between the members is expected. In this sense, neigh-
385 borhood overlap can be seen as a local support for the strength of a tie, and
386 therefore tie strength can be defined by this support. We denote the definition
387 of tie strength by neighborhood overlap as ‘Neighborhood Tie Strength’ (*NTS*).

388 Another important feature of a weak tie is its function as a ‘bridge’: a tie
389 that is the only connection between two communities. Granovetter suggests that
390 “no strong tie can be a bridge”, ergo bridges are always weak ties. Since, from a
391 global perspective, communities are generally connected via more than only one
392 tie, bridges are probably infrequent in practice. Granovetter therefore suggests
393 the more realistic idea of a ‘local bridge’ that has a specific ‘bridge degree’. In
394 particular, the degree of a local bridge increases as the number of alternative
395 paths between the members it connects decreases. Since local bridges between
396 isolated communities are an important concept in the ‘weak tie’-theory, it is
397 reasonable to define the strength of a tie by its bridge degree, which we denote

398 as ‘Bridge Tie Strength’ (*BTS*).

399 Since J. Milroy and L. Milroy describe a weak tie as i) being a relationship
400 of low intensity/multiplexity, ii) having a low local density and hence a low
401 neighborhood overlap, and iii) being an infrequent and abbreviating connection
402 between close-knit communities (a bridge), they describe a weak tie as a tie
403 with concurrently low *ITS*, *NTS* and *BTS* values. On the assumption that
404 the ‘weak tie’-theory is correct, there is a good case to believe that it would be
405 valuable to figure out which of these three tie strengths is mostly responsible
406 for innovation.

407 Analyzing the properties of a social network in a computational model re-
408 quires formalizing them. First, we consider a graph structure that allows for
409 determining tie strength in a direct way by providing each tie with a value,
410 generally called the weight of a tie.¹⁰ In this sense, a social network is defined
411 as a weighted graph (G), and $G = (M, T, w)$, where

- 412 i) $M = \{m_1, m_2, \dots, m_n\}$ is a set of n members
413 ii) $T = \{\{m_i, m_k\} | m_i, m_k \in M\}$ is a set of bidirectional ties
414 iii) $w : T \rightarrow (0, 1]$ is a weight function that labels each tie t with a weight $w(t)$,
415 where for all $t \in T : 0 < w(t) \leq 1$

416 Thus, the weight of a tie must be greater than 0 (otherwise it would be
417 absent) and at most 1. With these prerequisites the three types of tie strength
418 – Intensity, Neighborhood and Bridge Tie Strength – can be defined as follows:

Definition 1 (Intensity Tie Strength) *Given a weighted graph $G = (M, T, w)$.
The ‘Intensity Tie Strength’ *ITS* for a tie $t \in T$ is defined as follows:*

$$ITS(t) = w(t)$$

Definition 2 (Neighborhood Tie Strength) Let N_i be a set of neighbors (connected members) of a member $m_i \in M$. Then for a given weighted graph $G = (M, T, w)$ the ‘Neighborhood Tie Strength’ NTS for a tie $t = \{m_i, m_k\} \in T$ is defined as follows:

$$NTS(t) = \frac{|N_i \cap N_k|}{|(N_i \cup N_k) - \{m_i, m_k\}|}$$

Definition 3 (Bridge Tie Strength) Let P_{ik} be the set of all paths¹¹ between every two members $m_i, m_k \in M$, whereby the length¹² of a path p is given as $|p|$. Then for a given weighted graph $G = (M, T, w)$ the ‘Bridge Tie Strength’ BTS for a tie $t = \{m_i, m_k\} \in T$ is defined as follows:

$$BTS(t) = \frac{1}{1 + \sum_{p \in P_{ik}} \left(\frac{1}{|p|^2}\right)}$$

419 Having defined these three tie strength values, the next step is to investi-
 420 gate their impact on innovation. By assuming that weak ties are the source
 421 of innovation, it is still an open question as to which of the three tie strength
 422 measures contributes most. To that end, we implement here a game-theoretic
 423 network simulation model and analyze the contribution of each of the three dif-
 424 ferent tie strengths, under the assumption that these three values are completely
 425 independent.

426 As realistic social networks in human populations have small-world⁶ and
 427 scale-free⁷ properties (c.f. Jackson 2008), we constructed a scale-free network
 428 with such properties by a ‘preferential attachment’ algorithm (Holme and Kim
 429 2002). To have a weighted graph, each tie of the network was labeled with a
 430 randomly chosen value greater than 0 and maximally 1. The weight of the tie
 431 represents the probability with which each tie is used for communication per
 432 simulation step.¹³

433 During a simulation run, the members of the artificial society communicate
434 repeatedly with their immediate neighbors by way of a signaling game (Lewis
435 1969), with agents switching systematically between speaker and hearer roles.
436 In the implemented exemplar, members communicate three different concepts
437 to each other through a repertoire of maximally nine different message vari-
438 ants.¹⁴ The members also use a version of reinforcement learning (c.f. Bush
439 and Mosteller 1955, Roth and Erev 1995) to learn the optimal communication
440 strategy. So that innovation can emerge, members deviate from their current
441 strategy with a probability inversely proportional to the efficiency of the local
442 communicative success. This model reproduces a similar study by Mühlenbernd
443 (2014).

444 For the simulation experiments, we chose a scale-free network with 200 mem-
445 bers. We conducted 10 simulation runs, whereby one run entailed 100,000 sim-
446 ulation steps, and in one simulation step the signaling game was played on each
447 tie with the probability defined by its weight. Each simulation run started with
448 a number of pre-established regions of local communication norms (c.f. Figure
449 3). Members communicated repeatedly, updating their behavior as a function
450 of their previous success.

451 As a basic result, it turned out that innovation – in terms of a member using
452 a new communication system – emerged sporadically (0.04% of all cases of
453 communication) and sometimes spread to a fair amount of the network. Since
454 we were exclusively interested in the circumstances that support innovation
455 itself, and not spread, we computed the ‘innovative support’ *INV* of each tie.
456 The *INV* value of a tie t is defined by the proportion of events where a node
457 adjacent to t was innovative compared to the total of all communicative events
458 on t . In this sense *INV* represents the frequency of a tie being supportive to
459 innovation. By calculating the correlation of *INV* with the tie strength values,

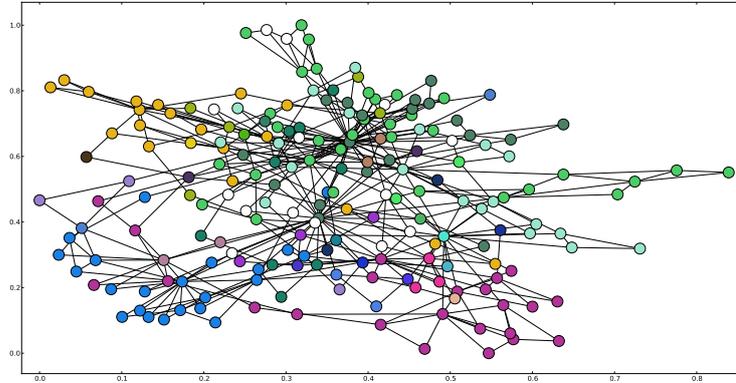


Figure 3: Exemplary scale-free network of 200 members, initially divided in pre-established regions (indicated by color)

460 (*ITS*, *NTS* and *BTS*) it was possible to deduce which property was most
 461 supportive for innovation, and whether there are significant correlations. The
 462 results are depicted in Figure 4 as scatter plots between *INV*, *ITS*, *NTS* and
 463 *BTS* (3940 data points).

464 A T-test revealed that there is no significant linear correlation between each
 465 combination. In a further step we computed the ‘Spearman’-correlations that
 466 detects non-linear correlations. To see if particular tie strength values might
 467 impact innovation, we then computed the correlations between *INV* and each
 468 individual tie strength, The results are given in Table 1: the only noteworthy
 469 result of the single tie strength values is the correlation between *INV* and *NTS*.
 470 In a further step we computed the *P* value for all combinations (Table 1) and

	<i>ITS</i>	<i>NTS</i>	<i>BTS</i>
<i>INV</i> : Spearman correlations	.05	-.3	-.02
<i>INV</i> : P values	.018	< .001	.19

Table 1: ‘Spearman’-correlations between ‘innovative support’ *INV* and the tie strengths *ITS*, *NTS*, *BTS* plus the possible combinations as products.

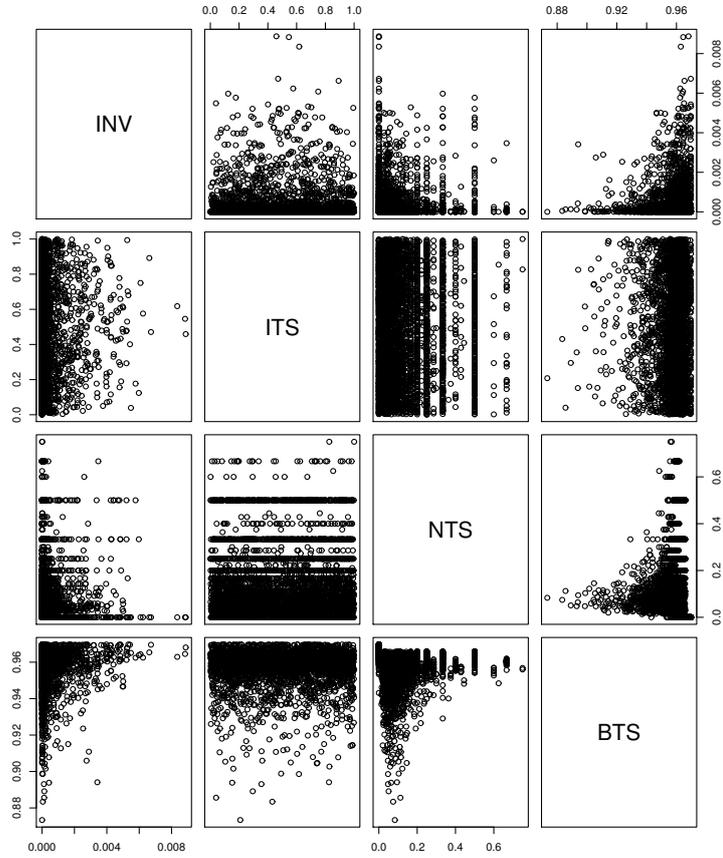


Figure 4: Scatter plots of combinations between ‘innovative support’ *INV* and tie strength values *ITS*, *NTS* and *BTS*

471 only the correlation between *INV* and *NTS* revealed an extremely low value
 472 ($< .001$) that is interpreted as absolutely highly significant. In other words:
 473 while we found no significant correlation between *INV* and *ITS* or *BTS*, we
 474 found a highly significant negative non-linear correlation between *INV* and
 475 *NTS*. Furthermore, the correlation reveals that *INV* increases exponentially
 476 with decreasing *NTS*, giving a power law ($x^{-\alpha}$) relationship. This result im-
 477 plies that as neighborhood overlap (*NTS*) decreases to particularly low values,

478 innovative support (*INV*) increases.

479 All in all, our virtual experiments endorse the ‘weak tie’-theory under the
480 assumption that tie strength is defined by ‘local support’ in terms of neighbor-
481 hood overlap.¹⁵ Conversely, the definition of tie strength in terms of i) ‘direct
482 support’ like the intensity of the tie usage, or ii) ‘global support’ like the ex-
483 istence of alternative ‘bridges’ both fail to endorse the ‘weak tie’-theory. This
484 result shows us that the formal precision required to implement these simula-
485 tions and their subsequent findings can help us unravel the candidates for the
486 drivers of sociolinguistic variation and change.

487 9 Conclusion & Outlook

488 We have detailed the various advantages of simulation approaches to language
489 change in an attempt to overcome the obstacles to lengthy and expensive cohort
490 and longitudinal studies. We have further highlighted the benefits of incorporat-
491 ing game-theoretic methods into social network analysis for this purpose. As an
492 example, we presented a study that endorses – under particular assumptions –
493 one of the dominant theories of sociolinguistic innovation: the ‘weak tie’-theory.

494 Although simulation studies cannot substitute for fieldwork, we argue for
495 their incorporation as a valuable supplement to it. We claim this is but the be-
496 ginning of the promise of game-theoretic methods combined with social network
497 simulations towards augmenting sociolinguistic theories of language change and
498 variation. In particular, theories like linguistic change spurred by competing
499 grammatical heuristics (Kroch 1989, Yang 2000) or partial blocking could lend
500 themselves nicely to simulations in pseudo-evolutionary environments. We em-
501 phasize once again, that these studies are not intended to replace field work, but
502 to open up the field of sociolinguistics to a new tool by which it might further
503 advance.

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Notes

¹In her book “Language and Social Networks”, 2nd edition, Milroy mentions on page 178: “Since all speakers everywhere contract informal social relationships, the network concept is in principle capable of universal application and so is less ethnocentric than, for example, notions of class or caste. [...] Since the network concept, unlike the socio-economic class, is not limited by intercultural differences in economic or status systems, it is a valuable tool of sociolinguistic analysis also.”

²The ‘weak tie’-theory is based on the assumption that members that are weakly connected to a social network are i) more likely to come into contact with new variants, and ii) less likely to conform to group norms. The ‘weak tie’-theory is empirically supported, for instance by Labov (1973) and L. Milroy (1980). Note that the opposed ‘strong tie’-theory (c.f. Jacobsen 1972) says that innovation emerges on strong ties. This is based on the assumption that i) new variants are mainly adopted from network leaders – central and influential members of a network with a high number of strong ties – since their variants are seen as more prestigious, and ii) network leader are more engaged with other leaders from other networks, thus are more likely to adopt new variants. Also the ‘strong tie’-theory has empirical support, e.g. by Labov (1989).

³Note that simulation studies without incorporating a network structure mostly abstract from this assumption, and each individual can interact with every other one in the society.

⁴Nettle sees linguistic items as ‘cultural traits’ (c.f. Cavalli-Sforza 1981, Robert and Richerson 1985), that are passed among generations and possibly changed over time by modification or even replacement through a competing item. In general, a linguistic item can be a semantic meaning, a syntactic marking strategy, a phoneme or anything else that represents a particular concept in of person’s language and can be transmitted via communication. Variants of an item are different manifestations of it. One example is the relationship between a phoneme (linguistic item) and the way it is communicated by different phones (variants of the phoneme).

⁵According to Latané’s (1981) ‘Social Impact Theory’.

⁶Generally speaking, small world networks require a low number of ties needed to connect two members chosen randomly, even if there is a high probability that these members are not connected directly. Formally, a small-world network is given by having two independent structural features: a high clustering coefficient (probability that nodes’ neighbors are connected), and a low average shortest path length (node-to-node distance).

⁷A scale-free network structure has a scale-free degree distribution: many nodes with a very low degree, and very few nodes with a very high degree. Such a structure emerges when new members are introduced via ‘preferential attachment’: they are more likely to connect to members of higher degree, producing a few local hubs of high connectivity and increasingly more nodes with lower connectivity; this gives the graph the scale-free property.

⁸Note that the scale-free property of the network structure ensures the existence of super-influential agents. Fagyal et al. (2010) made also experiments with the absence of such agents and showed that in such a case propagation was strongly limited to local regions.

⁹This is not surprising, since Lewis (1969) introduced signaling games even for the question of how semantic conventions emerge, under the assumption that there is no previous agreement.

¹⁰While Granovetter himself posited a discrete value for the strength of ties (strong or weak), his definition demands a continuous value, as L. Milroy (1980) remarks. We claim it necessary to consider tie strength as a continuous value and therefore define a network as a weighted graph.

¹¹A path in a network is a finite sequence of ties which connect a sequence of members which are all distinct from one another.

¹²The length of a path is defined by the number of members it connects.

¹³Note that to assign the weights to the ties randomly might not contribute to the realism of the network structure, since these weights represent the intensity of a connection, which is surely connected to further network features. But since i) the point of the experiment is to analyze the three tie strength values' impact on innovation independently of each other, and ii) intensity tie strength is defined by the weight of the tie, it is essential to assign this value randomly to ensure its independence from the other two values.

¹⁴These numbers were a compromise of a relatively large space of alternatives and low computational costs for the update mechanism.

¹⁵Admittedly, the low P value solely tells us that the correlation is highly likely not due to chance, so to detect the exact relationship between NTS and INV is a task for further analyses.