Original Articles

Social network size can influence linguistic malleability and the propagation of linguistic change

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ABSTRACT

We learn language from our social environment, but the more sources we have, the less informative each source is, and therefore, the less weight we ascribe its input. According to this principle, people with larger social networks should give less weight to new incoming information, and should therefore be less susceptible to the influence of new speakers. This paper tests this prediction, and shows that speakers with smaller social networks indeed have more malleable linguistic representations. In particular, they are more likely to adjust their lexical boundary following exposure to a new speaker. Experiment 2 uses computational simulations to test whether this greater malleability could lead people with smaller social networks to be important for the propagation of linguistic change despite the fact that they interact with fewer people. The results indicate that when innovators were connected with people with smaller rather than larger social networks, the population exhibited greater and faster diffusion. Together these experiments show that the properties of people's social networks can influence individuals' learning and use as well as linguistic phenomena at the community level.

1. Introduction

Imagine that you are trying to come up with a name for your band, and you are debating between Karaoke Dentist and Popcorn Logic.[1] If you were to ask one of your friends which name they prefer and they responded Karaoke Dentist, this might tilt you towards choosing this name. In contrast, if you were to ask twenty-one of your friends, and ten of them were to prefer Popcorn Logic and eleven, including that friend, had preferred Karaoke Dentist, this friend's preference of Karaoke Dentist is likely to not influence you that much. In other words, there is an inverse relationship between how many sources one has and how informative each source is. This relationship between sample size and informativity is a general principle and likely extends to linguistic information as well. Therefore, people who are exposed to linguistic input from many sources should be less susceptible to the influence of new incoming linguistic input compared with people who only interact with few people. Throughout this paper, the number of people someone regularly interacts with would be referred to as the person's social network size, and similarly, people who interact with many people regularly would be referred to as people with large social networks. The hypothesis that this paper tests then is that the larger people's social network, the less they would be influenced by exposure to a new

speaker. Such an argument has implications not only for our understanding of how people learn and update their knowledge, but also for language change, as it suggests that the spread of linguistic change might depend more on people with smaller rather than larger social networks. Study 1 test whether people's social network size influences the degree to which they are susceptible to the influence of a new speaker, and Study 2 describes simulations that test whether such differences in malleability could lead people with smaller social networks to be important for the propagation of linguistic change.

1.1. Communication accommodation

When people interact, their language tends to align across all linguistic levels (e.g., Giles, Coupland, & Coupland, 1991). For example, it has been found that during interaction people accommodate their pitch, speech rate, frequency and duration of pauses, standardness of speech, lexical choices, grammatical choices, and even nonverbal mannerisms, to those of their interlocutor (Branigan, Pickering, & Cleland, 2000; Brennan & Clark, 1996; Chartrand & Bargh, 1999; Coupland, 1980; Gregory & Webster, 1996; Jaffe & Feldstein, 1970; Street, 1982; Thakerar et al., 1982). In fact, even though social factors seem to modulate some of these effects (e.g., Babel, 2012; Giles et al., 1991;

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[1] Names generated by www.wordlab.com/name-generators/band-name-generator.

Gregory & Webster, 1996), passive exposure without any interaction can also increases alignment (e.g., Bock, 1986; Goldinger, 1998). Such alignment has been theorized to reflect learning and thus lead to long-term convergence (Bock & Griffin, 2000; Chang, Dell, & Bock, 2006). For example, the speech of previously-unfamiliar college roommates has been shown to become more similar after living together (Pardo, Gibbons, Suppes, & Krauss, 2012). More generally, it has been argued that we use incoming input to update our priors, and thus, as the statistics of our environment change, so do our representations (Jaeger & Snider, 2013).

1.2. Majority learning

Language learning can be seen as a type of social learning. One typical characteristic of social learning is the conformity bias, that is, preferentially copying behaviors that are frequent in the population (e.g., Boyd & Richerson, 2005). Importantly, people are not simply sensitive to the raw frequency of a certain behavior, but also the number of sources that exhibit it. Having five different friends vote for Karaoke Dentist is more informative than having the same friend vote for Karaoke Dentist five times. Indeed, even chimpanzees (though not orangutans) are more likely to adopt a behavior when it is performed by two out of three demonstrators, than when it is similarly performed two thirds of the time, but always by the same demonstrator (Haun, Rekers, & Tomasello, 2012). Three to 6 year-old children have also been found to imitate an action more when it is performed by two demonstrators than when it is performed by a single demonstrator twice (Herrmann, Legare, Harris, & Whitehouse, 2013).

One consequence of gathering information across many sources is that the weight ascribed to each source should decrease with the increase in number of sources. Consequently, the same input should be weighed differently by people who are exposed to different number of sources. Note that this argument doesn't necessitate that sources are given equal weight. Even if we assume that we ascribe greater weight to the input that we receive from some people than from others, it is still the case that, on average, sources should be assigned lower weight the more of them we have. This should lead people with smaller social networks to assign greater weight to each person they encounter, and therefore to be more susceptible to each person's influence.

Some initial evidence suggests that this is the case. In particular, one previous study found that the smaller the participants' social network, the more they shifted their phonological boundary between /d/ and /t/ following exposure to a speaker with atypical productions (Lev-Ari, 2017). Furthermore, a control condition which tested participants on their learning of the phonological boundary of the exposure speaker and not on the change in their own boundary, ensured that participants' ability and motivation to learn the speaker's speech pattern did not depend on their social network size. That is, participants with large and small social networks learned the speaker's speech patterns equally well, but those with larger social networks were less likely to generalize it and adjust their own general representation. This previous study thus suggests that social network size can influence how susceptible people are to the influence of new speakers. The current study goes beyond the previous findings in several ways. First, the previous study focused on perception. In order to link representational malleability to language change, it is important to examine the influence of social network size also on production. The current study tests the influence of social network size on both prediction and production. Additionally, the previous study focused on the phonological level, whereas this study focuses on the lexical level.

1.3. Language change

Languages constantly change. The word *douchebag*, the use of *because* to introduce a noun-phrase, a shift towards *more* constructions over *-er* constructions for comparatives, and speaking with a vocal fry are all instances of linguistic innovations that have gained popularity in recent years. In general, language is not a uniform phenomenon, but consists of great heterogeneity of variants and patterns. In many cases, however, this variation does not lead to linguistic change, as the variants do not propagate through the community (e.g., Weinreich, Labov, & Herzog, 1968). This paper proposes that people with smaller social network might play a particularly important role in propagating the diffusion of linguistic variants. This proposal might provide a partial solution to the threshold problem (Nettle, 1999) – the puzzle regarding how innovations, which are rare by definition, can spread through the community when speakers tend to use the most common variant they have encountered. One way of overcoming this problem is by assuming that speakers do not simply copy the most frequent variant, but that they hold some biases, leading them to be more likely to copy variants that are better in some way or that are used by more prestigious speakers (Nettle, 1999). The hypothesis tested in this paper adds that the threshold problem is also easier to overcome by speakers with small networks.

Previous research on linguistic diffusion tended to focus on identifying the innovators rather than those propagating the innovation (e.g., Fagyal, Swarup, Escobar, Gasser, & Lakkaraju, 2010; Labov, 2001; Milroy & Milroy, 1985). Interestingly, those who did investigate diffusion, especially diffusion of information and behavior, assigned a central role to diffusion via weak ties, that is, via relationships that are low in frequency and intensity (Bakshy, Rosenn, Marlow, & Adamic, 2012; Granovetter, 1973; Mühlenbernd & Franke, 2012; Weimann, 1982). This research thus shows that non-central members could be crucial for the diffusion of behavior, and suggests that people with small social networks could play an important role in diffusing linguistic change despite their non-central role in the community.

2. Experiment 1

The aim of Experiment 1 is to test whether individuals with smaller social networks have more malleable linguistic representations. The malleability of individuals' linguistic representations was measured by testing the degree to which their general lexical boundary between *some* and *many* has changed as a consequence of exposure to a speaker whose lexical boundary differs from their own. Yildirim, Degen, Tanenhaus, and Jaeger (2016) have shown that people can learn a speaker's boundary between *some* and *many*. The paradigm used in Experiment 1 was loosely based on their paradigm with some modifications to render it analogous to the perceptual learning paradigm used in Lev-Ari (2017). In addition, a production test was added. Participants were exposed to a speaker whose boundary between *sommige* and *veel* (*some* and *many* in Dutch, respectively) differed from theirs by two steps. Then participants estimated which label a new speaker would use to describe new scenarios. The hypothesis was that participants' social network size would modulate the degree to which they would generalize the speaker's boundary to a new speaker, such that having a larger network would lead to lower generalization.

One limitation of this design is that people are not randomly assigned into social network size, and therefore it could be that people of different social network sizes differ in the way they approach the task, in their motivation to do the task, or even in their ability to learn the speech patterns of the speaker. Therefore, the experiment included a control condition in which participants estimated how the speaker they were exposed to would describe new scenarios. Unlike the case of a novel speaker, this condition examines whether participants are able to learn the linguistic patterns of a specific speaker. The hypothesis is that participants' social network size would not influence this ability, as having more sources should not impair the ability to learn lexical boundaries per se, but should only influence the informativity of the input for the wider population. Therefore, as long as individuals are given the same amount of information about a particular speaker's linguistic patterns, their social network size should not influence their

ability to learn the speaker's patterns. Finding that social network size modulates learning in the New Speaker condition but not in the Same Speaker condition would thus indicate that social network size modulates the degree to which people adjust their general representation in response to exposure, and that this effect is not due to differences in ability to learn the pattern.

Additionally, participants were tested on the influence of the exposure speaker on their own production by asking them to describe a new set of scenarios using the labels *sommige* and *veel* and comparing their boundary to the one they had in the baseline test, before they were exposed to the speaker. The prediction was that in this case as well, the smaller participants' social network, the more they would shift their boundary in the direction of the exposure speaker.

2.1. Method

2.1.1. Participants

One-hundred-seventy-nine native Dutch speakers were recruited, mostly university students (F = 140; Age: 18–38, M = 22, SD = 2.7.[2]) They were paid 6 Euros for their participation.

2.1.2. Stimuli

Multiple arrays of 25 purple and green stars were generated (see Fig. 1). The number of purple stars in the array ranged from two to 24. One speaker was recorded saying the sentences: *Sommige sterren zijn paars* (=some of the stars are purple) and *Veel van de sterren zijn paars* (many of the stars are purple) many times. Two photographs of two college-aged Dutch women were used to represent the speakers.

The social network questionnaire was identical to the one used in Lev-Ari (2017). Participants were asked to list all the people they talk to in a regular week. They were instructed to only include interlocutors above the age of 12 with whom they interact for at least five minutes. For each interlocutor, participants indicated the total duration of their typical interactions with them. This information enabled distinguishing the effect of social network size (no. of interlocutors) from amount of input (no. hours of interaction). Participants also specified for each interlocutor their age. Lastly, participants indicated which members of their network regularly talk to each other.

2.1.3. Procedure

The experiment was composed of four phases. First, participants' baseline boundary between *some* and *many* was measured. This phase is an addition to Yildirim et al.'s (2016) procedure. Its goal is to allow to cleaner, easier-to-interpret results, as well as increase power. As participants differ in their baseline boundary, assigning them to one of the conditions without knowing their baseline could lead some participants to be exposed to a boundary that is in fact not different from their own. In such a case, later predictions and productions that are in line with their exposure might also be in line with their baseline boundary and not reflect learning. In contrast, by knowing what participants' boundary is and adjusting exposure to that, one can be certain that what the test indeed measures a shift from baseline. Participants' baseline boundary was measured by presenting them with 23 star arrays, and asking them which of two written sentences *Sommige sterren zijn paars* (=some of the stars are purple) and *Veel van de sterren zijn paars* (many of the stars are purple) is the best description for the array. Participants indicated their response by pressing "1" for the *some* version, and "2" for the *many* version. In the real world, additional quantifiers might be used to describe such arrays (e.g., several, most). Such alternative quantifiers were not provided to participants though, because the hierarchy of all possible quantifiers is not always clear, and some of them overlap in the range they cover. Therefore, including all
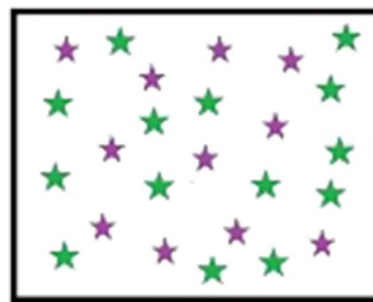
Fig. 1. Example of a stars array used in Experiment 1.

possible quantifiers would make it difficult to interpret and analyze the results. The restriction to only two labels might enhance the effect of learning, but this potential general enhancement is orthogonal to the predictor of interest, social network size. The arrays showed one of each possible combination of purple and green stars between two purple stars and 23 green stars, and 24 purple stars and one green star. Arrays' order of presentation was random. During this baseline phase, the computer calculated how many *some* responses a participant provided, and according to that, assigned the participant to a condition in which the exposure speaker's boundary was two steps further than the participant's. For example, if the participant shifted from using *some* to using *many* once there were 12 purple stars, they were assigned to a condition in which the speaker's boundary was at 14 purple stars. Participants' average boundary was 12.54 stars (range: 8–17, SD = 1.72), and did not differ between participants in the Same Speaker and New Speaker conditions (12.39 and 12.69, respectively) nor did it correlate with social network size (r = −0.07, p > 0.3). For seventeen participants, the likelihood of using *many* over *some* did not increase monotonically with the number of purple stars, which led to assignment to a wrong condition. They were therefore excluded. One participant had a boundary that was so high (17) that they could not be assigned to an exposure condition that was two steps further from their boundary. That participant was therefore also excluded.

Following the baseline test, participants were exposed to the speaker. During the exposure phase, participants saw 32 new star arrays. These appeared in the center of the screen. The number of purple stars in the array ranged from two to 24, such that each number on the range of 9–17 appeared twice, and all other options appeared once. The range of 9–17 was repeated twice, as the boundary between *some* and *many* falls there. In the corner of the screen, a photograph of a college-aged Dutch woman appeared. Participants were told that she was the speaker. 300 ms after the appearance of the screen, an audio file started playing. According to the number of purple stars and condition, the audio recording either said *Sommige sterren zijn paars* (=some of the stars are purple) or *Veel van de sterren zijn paars* (=many of the stars are purple). Each recording was unique. To ensure that participants pay attention, there were four catch trials, after the 4th, 7th, 15th, and 21st trials. In two of these catch trials participants were shown an array and were asked whether this was the array on the previous trial. In the other two catch trials, participants were asked which label, *sommige* (=some) or *veel* (=many), the speaker has just used. Seven participants answered at least two out of four catch trials incorrectly, and were therefore excluded from all analyses.

Following exposure, participants were tested. Participants were told that their task is to predict the description that a speaker would use to describe a novel array. Half of the participants were asked about the same speaker they listened to during the exposure phase (Same Speaker condition). The other half were asked to predict the responses of a different speaker (New Speaker condition). In both conditions, a picture of the speaker for which participants were predicting appeared to the left of the array. In the Same Speaker condition, this was the same picture as in the exposure phase. In the New Speaker condition, this was
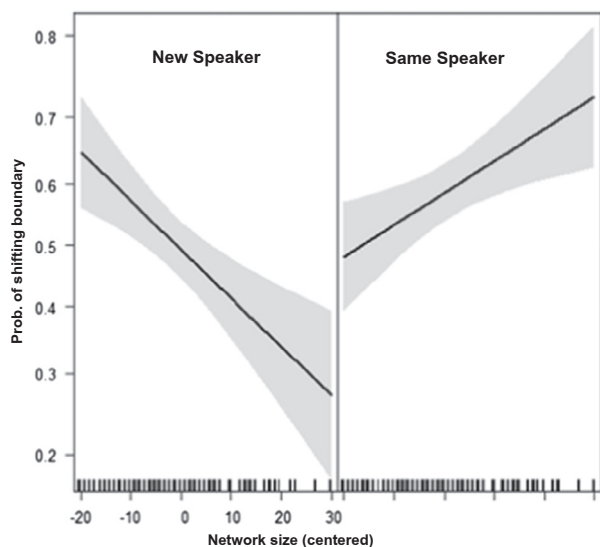
Fig. 2. The effect of Social Network Size on the magnitude of the influence of the exposure speaker (more *some* responses = greater boundary shift) as dependent on Speaker condition. Gray bands indicate 67% Confidence Interval. Note that the effect in the New Speaker is significant while the effect in the Same Speaker condition is not.

a picture of a different Dutch college-aged woman. Immediately above the picture of the stars array, one of the two sentences appeared. Participants needed to indicate whether this is the sentence that the speaker would use to describe the array or not by pressing P for *yes*, and Q for *no*. There were a total of 30 new arrays, such that the number of purple stars ranged between 2 and 24, with each option in the range of 9–15 appearing twice (once with *some* phrasing, and once with *many* phrasing), and all other options appearing once. Magnitudes outside the critical region appeared mostly with the predicted phrasing: all but two items in the pre-boundary region appeared with *some* phrasing, and all but two items in the post-boundary region appeared with *many* phrasing.

After completing the first test phase, participants were tested on their production. This test was identical to the baseline phase, except that the specific star arrays were new. That is, participants saw arrays of 25 stars similar to the one depicted in Fig. 1. As in the baseline phase, the ratio of green and purple stars ranged from two purple stars and 23 green stars to 24 purple stars and one green star. Participants' task was to indicate which of the two written descriptions, *Sommige sterren zijn paars* (=some of the stars are purple) and *Veel van de sterren zijn paars* (many of the stars are purple), fits the array better. Participants indicated their response by pressing '1' for the *some* version and '2' for the *many* version. This task differs from ordinary production tasks in that participants are forced to choose between two alternatives. This was done to shorten the task.

Finally, participants answered a questionnaire about their social network. Social network size ranged from 3 to 115 (M = 25). Three participants whose social network size was more than 2.5 Standard Deviations from the mean were excluded. One additional participant was excluded because a computer failure led to loss of their social network information. The social network size of the remaining participants ranged from 3 to 62 (M = 24).

2.2. Results

Data used in all analyses is provided in Supplementary Material. Analyses were conducted over the remaining 150 participants. First, it was tested whether social network size modulates participants' susceptibility to the influence of the exposure speaker when predicting speakers' language use. To do so, a logistic mixed model analysis was run over the trials with a number of purple stars for which the exposure

speaker's description differed from the participant's baseline response.[3] The analysis focused on these trials, as these are the only trials in which the influence of exposure can be seen. The mixed model included Participants as a random variable, and No. of Stars, Network Size, No. of Hours, Speaker (Same, New), an interaction between No. of Hours and Speaker, and an interaction between Network Size and Speaker as fixed factors. No. of Hours was included to ensure that any obtained effect is due to the number of sources people have (Network Size) and not to amount of input they receive (No. of Hours). The dependent measure was participants' response, such that predictions that the speaker would use the label *many* were coded as 0, and predictions that the speaker would use the term *some* were coded as 1. On all trials in which baseline response differed from the exposure speaker's use, it was the participant who used the label *many* and the exposure speaker who used the term *some*. Therefore, an influence of exposure would manifest in more *some* responses.

Results showed an effect of No. of Stars, such that the more purple stars there were in the array, the less likely participants were to predict that the speaker would use the term *some* ($\beta = -0.48$, SE = 0.08, $z = -5.84$, $p < 0.0001$). Crucially, the results also showed the predicted interaction between Network Size and Speaker ($\beta = -0.05$, SE = 0.02, $z = -2.18$, $p < 0.03$; see Fig. 2 and Appendix A). To better understand the interaction, separate analyses were run on the Same Speaker and New Speaker conditions. In the Same Speaker condition, the only significant predictor was No. of Stars ($\beta = -0.66$, SE = 0.12, $z = -5.45$, $p < 0.0001$), which indicated that participants were more likely to predict that the speaker would say *some* when there were fewer purple stars in the picture. In contrast, in the New Speaker condition, as predicted, participants' social network size predicted the magnitude of the influence of the exposure phase on their performance, though the p-value was just on the threshold of conventional significance ($\beta = -0.03$, SE = 0.01, $z = -1.96$, $p = 0.05$). Specifically, the larger participants' social network, the more likely they were to maintain their use of the term *many* and not shift to *some*. Additionally, there was an effect of No. of Stars ($\beta = -0.42$, SE = 0.08, $z = 5.07$, $p < 0.0001$), such that the fewer purple stars there were in the array, the more likely participants were to use the term *some*. The number of hours of interaction that participants have per week did not influence participants' behavior in either condition. These results thus show that participants' social network size indeed influences the degree to which they are susceptible to the influence of speakers they encounter. Furthermore, the fact that the effect of social network size was restricted to the New Speaker condition shows that it is not the case that participants with different social network sizes differed in their ability to do the task, or in their motivation. In addition, note that the intercept was significantly different from 0 at the baseline level, which was set to the Same Speaker condition. This indicates that participants showed learning in the Same Speaker condition. As reported above, Network Size did not influence this tendency. It is only when participants were tested about their generalization of the learned pattern to a new speaker that those with larger social networks were more reluctant to show influence of

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[3] One may wonder if it is worth examining the entire range and not only the steps for which exposure differs from production. There are several reasons not to do that. From a practical point, it is unclear how to analyze such cases. In the critical region *some* responses reflect a shift, and *many* responses reflect consistency with baseline. If all values are analyzed together, both *some* and *many* responses could be in the direction of exposure or away from it. Furthermore, all responses could reflect either both learning and consistency with baseline or neither, since outside the critical region, the two did not differ. Additionally, deviations from baseline were very rare outside the critical region, as, predictably, participants had no reason to shift considering the fact that exposure was consistent with their baseline. In general, participants showed such shifts on 9% of trials in the Same Speaker condition, 7% of trials in the New Speaker condition, and 3.5% of trials in the Production phase. Note that these shifts include hyper-learning (shifting the boundary beyond the speaker's) as well as errors, such as wrong key presses (e.g., naming an array with 24 purple stars *some* despite naming the entire range between 13 and 23 with *many*).
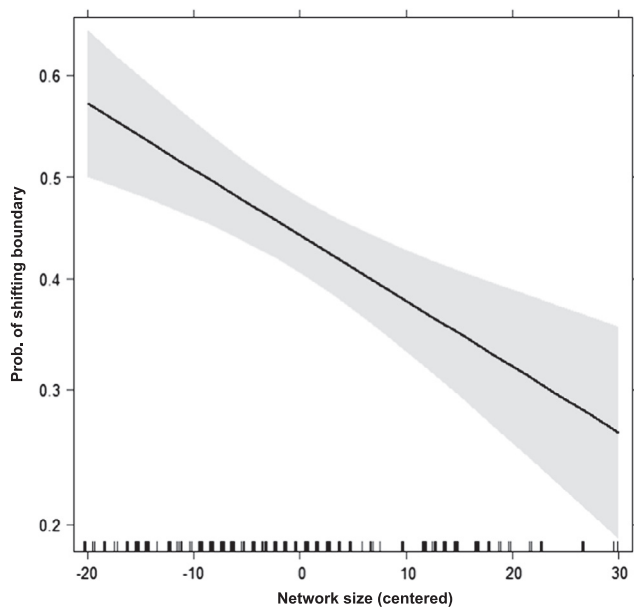
Fig. 3. The effect of Social Network Size on the magnitude of the influence of the exposure speaker (more *some* responses = greater boundary shift) on production. Gray band indicates 67% Confidence Interval.

exposure. One might expect the learning to be larger in the Same Speaker than in the New Speaker condition. This was the case numerically - participants shifted their boundary in 59% of the cases in the Same Speaker condition, but only in 48% of the cases in the New Speaker condition. This effect, however did not reach significance (p = 0.16).

Next, it was tested whether social network size also modulates the effect of exposure on participants' production. A logistic mixed model analysis with Participants as random variable, and No. of Stars, Network Size, and No. of Hours as fixed factors was conducted. As with the prediction task, the analysis focused on the range for which the exposure speaker's responses differed from the participant's responses at baseline. The dependent measure was whether the participant used *some* (a shift, coded as 1), or *many* (maintenance of baseline boundary, coded as 0). The analysis revealed a main effect of No. of Stars ($\beta = -0.60$, SE = 0.09, z = -7.07, p < 0.0001), and the predicted effect of Network Size ($\beta = -0.03$, SE = 0.01, z = -2.06, p < 0.04; see Fig. 3). Participants were more likely to use the term *some* the fewer purple stars there were in the array. Importantly, they were also more likely to use the term *some*, showing greater influence of the exposure speaker, the smaller their social network was.

The results of Experiment 1 thus show that people's social network size influences their susceptibility to the influence of a new speaker they encounter. It influences both their expectations of what novel speakers would say as well as their own productions. This experiment thus provides support for the proposal that the smaller people's social network, the more malleable their representations are. It thus suggests that people with smaller social networks might be particularly important for the propagation of linguistic change.

The design of this experiment contrasts *some* with *many*. As mentioned earlier, in the real world, there are additional alternatives one could decide to use, such as *several* or *most*. Therefore, one may wonder whether responding *no* to the question whether the speaker would use *many* to describe an array is comparable to saying that the speaker would use *some*, or whether a negative response can indicate consideration of alternative options as well. In other words, the analysis in this paper treats *no* responses to *many* as equivalent to *yes* responses to *some*, yet the two responses might not be equivalent pragmatically. Indeed, an alternative analysis of the results that includes Form (some, many), in addition to all other effects, provides some support for the

claim that the two responses might not be identical. In particular, such an analysis shows that participants were more likely to reject *many* than to endorse *some* ($\beta = -0.45$, SE = 0.2, z = -2.27, p < 0.03). Importantly all other effects, including the interaction of Social Network Size and Speaker, remained significant in this analysis, indicating that the effect of Social Network Size holds even after the effect of Form is accounted for.

Nevertheless, one may wonder whether it is justified to collapse over both forms in the analysis. There are several reasons to think so. First, the design of the experiment makes it abundantly clear to the participants that only two labels are permitted. All participants performed the baseline phase in which they could only choose between the labels *some* and *many*. The exposure phase also contained only these two forms, and participants were explicitly told that the speaker they were listening to had the same task as they did, namely, describe the arrays using one of the two terms. Therefore, by the time participants performed the prediction task, they were well aware that a speaker who did not use the term *many* necessarily used the term *some* and vice versa, and that no other options were available to the speaker. Secondly, the results of the prediction task and the results of the production task show the same pattern of results, even though the production task did not include the same ambiguity, suggesting that both tasks reflect the same shift in lexical boundary. Lastly, participants' pattern of responses is qualitatively similar across the two forms (see Appendix B). Together, these suggest that in the context of the experiment, participants' responses to the two forms can be analyzed together, and both are likely to measure a shift in lexical boundary. Furthermore, it's important to note that any possible effect of form is orthogonal to the finding that participants with larger social networks are more likely to maintain their baseline responses despite demonstrating equal learning of the speaker's use in the Same Speaker condition.

One may wonder though whether the fact that people with smaller social networks are more malleable is enough to enable them to play an important role in the diffusion of linguistic change. After all, people with smaller networks will also be able to influence fewer other people. To test whether the greater malleability of people with smaller social networks could be enough to lead them to be important for the spread of linguistic change, in experiment 2, computational simulations of a linguistic change were run in which the mutators (i.e., the innovators) were connected to either agents with small social networks or agents with large social networks.

3. Experiment 2

Experiment 2 tests whether the findings from Experiment 1 could have implications for the process of language change. Specifically, Experiment 2 assumes the results of Experiment 1, namely, that people with smaller social networks have more malleable representations. It tests whether that could lead them to play an important role in the propagation of linguistic change despite the fact that they are, by definition, connected to fewer people, and therefore, could have a direct influence on fewer members of the language community. To test this, a process of phonetic merge was simulated, such that in each simulation, 1% of the population merged two vowels (mutators). These mutators were connected to people whose social network size was either particularly low or particularly high. Interactions between people in the community were then simulated, and the distance between the vowels across the entire community was monitored to see how the mutators' network influences the rate and degree of convergence.

3.1. Methods

A population of 1000 agents was created using an Albert Barabasi algorithm from the Python NetworkX package (Hagberg, Schult, & Swart, 2008). This algorithm creates networks with a free-scale

structure. In such networks the distribution of agents' network size follows a power law. This structure is argued to be representative of the organization of real-world communities (Barabási & Albert, 1999).[4] All agents in the community knew two Dutch vowels, /ɑ/ and /a:/. While these vowels are mostly distinguished by duration, they also differ in their spectral properties. Each agent was ascribed mean formant frequencies for these two vowels according to published data about the formant frequency distribution of these vowels in the population (Pols, Tromp, & Plomp, 1973). Then, 10 agents out of the population were selected to be mutators, such that in 100 simulations, these mutators were connected to agents whose average network size was in the top 10% of the population (Neighbors with Large Social Network), and in 100 simulations these mutators were connected to agents whose average network size was in the bottom 10% of the population (Neighbors with Small Social Network). For these mutators, the /a:/ category was defined to be a copy of their /ɑ/ category. Then 50,000 rounds of interaction were simulated. In each round, each agent in the population interacted with at least one randomly sampled member of their network. Some agents interacted with more than one other agent if more than one member of their network sampled them as an interlocutor.[5] During each interaction, each agent produced one token of each vowel by sampling a token around their mean formant frequencies. Each interlocutor then updated their vowel categories to include the token they heard from their interlocutor. The new token was integrated with their prior vowel values by ascribing it a weight of 0.1/(agent's network size), and ascribing their previous knowledge the weight (1–0.1/(agent's network size)). The weight ascribed to the new token implemented the inverse relationship between network size and the weight ascribed to each speaker in the network. After every 5000 interactions, the distance between the vowels across all members in the community (excluding mutators) was measured.

3.2. Results

The results of the simulations used for the reported analysis are provided in the Supplementary material. A mixed model analysis was conducted to test whether, given the inverse relationship between network size and representational malleability, people with small social networks can be important for language propagation despite being connected to fewer people. The model was run on the log distance between the two vowels in the community, as dependent on the size of the network of the mutators' neighbors (Neighbors with Small Social Network, Neighbors with Large Social Network), Time (coded as number of interactions in intervals of 5000), and their interaction. One problem with such an analysis is that in scale-free networks, there is preferential attachment, such that agents have higher likelihood of being connected to agents with many neighbors. This property of the network means that agents who have Neighbors with Small Social Networks are likely to have much larger networks than the average agent, because links to Neighbors with Small Social Networks are only added after links to Neighbors with Large Social Networks were added. Therefore, the predicted effects of greater and faster merger of the
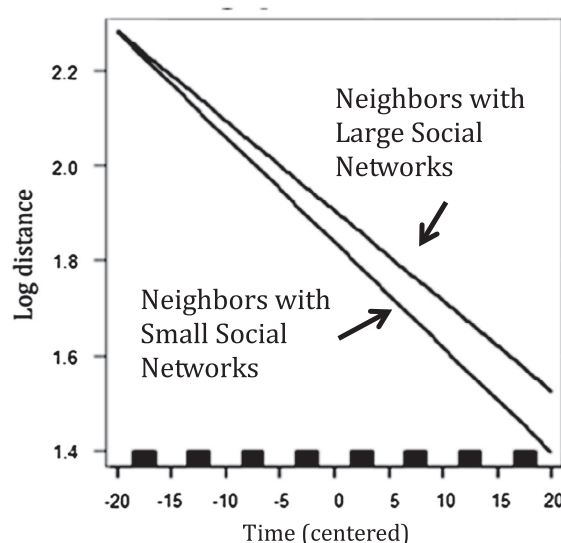
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[4] The distribution of social network sizes in the sample of participants in Experiment 1 did not follow a power law but was similar to a normal distribution but with a long right tail. The same distribution has been found in previous studies (e.g., Lev-Ari, 2016). It is unclear whether real world communities do not always follow the predicted power law or whether experimental samples are not representative. Either way, scale-free structure was used here to keep in line with previous literature and maintain other theoretically-motivated characteristics of real-world communities.

[5] Interlocutor choice was biased towards selecting those who have yet to be selected by others, but did not preclude such multiple selections, as doing so would bias some agents to always interact with the neighbors who have small networks rather than those with large social networks. Note that if the occasional unequal number of interactions per agent influences the results, then its influence would be to increase the importance of agents with larger social networks over agents with smaller social networks, and would thus go against the tested hypothesis.

Fig. 4. Log distance between the two vowels as a function of Time (i.e., number of interactions divided by 100) and Mutators' Network (Neighbors with Large Social Networks, Neighbors with Small Social Networks). Gray confidence interval bands are imperceptible because the Standard Error is very low.

vowels when mutators have Neighbors with Small Social Network could arise from the fact that mutators with such neighbors are probably connected to more people, and can thus infect more people, and not be due to the greater malleability of agents with small networks. To control for this possibility, the model also included a factor measuring the Number of Infected members, that is, the number of agents who are directly linked to a mutator. In addition, the model included Simulation No. as a random variable. The random structure included an intercept and a random slope for Time.

Results revealed a main effect of Time ($\beta = -1.90e-2$, SE = $1.78e-4$, t = -106.6), such that the distance between the vowels decreased with Time. Results also showed an effect of No. Infected ($\beta = -3.85$, SE = $6.50e-5$, t = -5.92) reflecting the fact that the distance between the vowels was smaller the more infected agents there were. Importantly, results revealed the predicted effect of Mutators' Network (Neighbors with Small Social Networks: $\beta = -6.49e-2$, SE = $6.94e-3$, t = -9.36) indicating that there was greater convergence between the vowels when mutators had Neighbors with Small Social Network. Additionally, results revealed an interaction between Time and Mutators' Network ($\beta = -3.175e-3$, SE = $2.52e-4$, t = -12.6; see Fig. 4 and Appendix C), such that Time had a bigger effect (faster convergence) when mutators had Neighbors with Small Social Network. To summarize, Experiment 2 indicates that given greater malleability, people with small social networks could play an important role in the propagation of linguistic change despite being able to directly influence fewer people.

4. General discussion

Together, these studies show that individuals with smaller social networks have more malleable representations, and that this greater malleability can lead them to play an important role in the propagation of linguistic change. Specifically, Experiment 1 shows that those with smaller social networks are more likely to adjust their lexical boundaries following exposure to new input. These results are in line with the proposal that the inverse relationship between number of sources and the informativity of each source leads those who are exposed to fewer sources to be more susceptible to the influence of each new source they encounter. The results of Experiment 2 suggest that this greater malleability could lead people with smaller social networks to play an important role in the propagation of linguistic change. In that study, the

change was greater and faster when mutators were connected to agents with smaller networks than when they were connected to agents with larger social networks.

One caveat is that individuals' social network size in Experiment 1 was not manipulated but reflected natural variation in network size. Therefore, theoretically, any effect that was found could be due to causality in the opposite direction or to co-variation with another factor. While this cannot be ruled out completely, the specificity of the effect to the New Speaker condition makes it unlikely to be the case. The lack of an effect of social network size in the Same Speaker condition indicates that people of different social network sizes approached the task similarly and were equally able to learn the linguistic patterns. Furthermore, the lack of an effect of social network size in the Same Speaker condition cannot be due to insufficient power, since there was enough power to reveal the opposite direction in the New Speaker condition, and, if anything, the numeric pattern in the Same Speaker condition went in the opposite direction to that in the New Speaker condition. Anecdotally, the same nonsignificant numeric trend in the opposite direction was also found in the Same Speaker condition in Lev-Ari (2017). As this numeric trend of social network size in the Same Speaker condition is not significant, it will not be discussed in detail. One possibility is that having a larger social network improves one's ability to learn speakers' linguistic patterns. Indeed, previous studies have found that having a larger social network improves comprehension of others (Lev-Ari, 2016). In general, input from a larger social network tends to be more variable (Lev-Ari, 2018) and input variability has been argued to assist in learning which dimension to attend to (Posner & Keele, 1968; Rost & McMurray, 2010). Thus, the numerical trend might reflect such a boost of network size on learning. This would make it even more remarkable that despite superior learning of the speaker's speech pattern, participants with larger social networks generalize it less. Importantly, regardless of the underlying cause of the social network effects that were found, the results of this paper show a relevant and ecologically important pattern, that people with smaller social networks have more malleable linguistic representations. They point to the potentially large role that non-hub members have in propagating changes, leaving open the question regarding how people self-select into developing different types of social networks.

These results relate to the threshold problem in language change - the puzzle regarding how rare forms, especially ones that do not have any obvious advantage, get adopted and diffuse through the network (Nettle, 1999). While social network size cannot account for such diffusion on its own, combining small social network size with other assumptions, could. For example, it has been suggested that novel forms attract more attention and increase learning, and this can lead recent input to be assigned relatively high weight, leading to greater shifts in early stages of learning with novel forms (Chang, 2013). Similarly, other factors, such as the social status of the speaker, might play a role

as well and help boost learning further in some cases, leading those with smaller network to be more likely to go over the tipping point and adopt novel forms (Nettle, 1999).

One might wonder how the results of this study depend on the stability of a boundary. In the real world, our use of the labels *some* and *many* might differ across contexts. Similarly, across different contexts, we will produce different formant frequencies for the same vowel. In the studies here the situation was simplified. In Experiment 1 the context remained stable, and the simulations in Experiment 2 did not include any context, though they included intra-individual variability. Context-based conditioning is likely to make the learning task more difficult. It is unclear though whether it would change the main patterns. When processing input, learners are likely to not only consider the frequency of that form but more specifically the frequency of that form in such a context. This would suggest that the greater variability there is across contexts, the more important it would be for learners to have had exposure to multiple types of contexts. Correspondingly, representational malleability would be inversely correlated to both the number of sources people have been exposed to (social network size) and to the number of different contexts they have experienced. Therefore, when variability across contexts is high, those who tend to interact with people in a very narrow set of circumstances might also play a relatively large role in the propagation of linguistic changes, as their representations would be more malleable when presented with use in new contexts. Further research should therefore examine both aspects of past experience - social network size and contextual variability - to get a fuller picture of learning and propagation of innovations.

It is important to note that the studies in this paper focused on vulnerability to novel input that carries no social meaning. That is, the use of the terms *some* and *many* is not associated with any social marker or sub-group. Many linguistic changes seem to fall under this type. For example, changes that are due to structure re-analysis or sound misperception are often socially neutral. Other changes such as the shift in English comparatives towards higher frequency of *more* over *–er* constructions (Hilpert, 2008) also seems to be socially neutral. That said, some innovations are highly noticeable and associated with different social identities. The results of our studies are most relevant to more socially neutral and unnoticeable changes. The number of sources and the statistical weighting are likely to be more pertinent when an explicit wish to project a certain identity and avoid another are irrelevant, and when the learning is mostly implicit. It is an interesting question how social network size interacts with social factors in cases where linguistic innovations are more marked and socially motivated.

To conclude, these studies show that individuals' social network size influences how malleable their linguistic representations are. It thus suggests that individuals with small social networks might play an important role in the propagation of linguistic innovations.

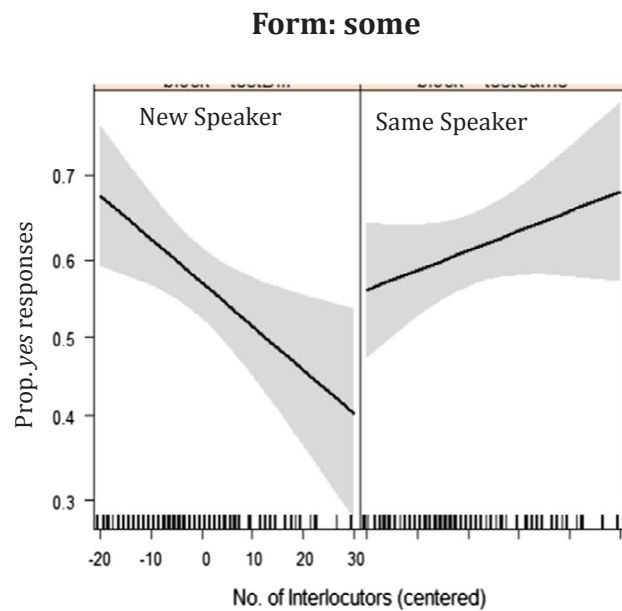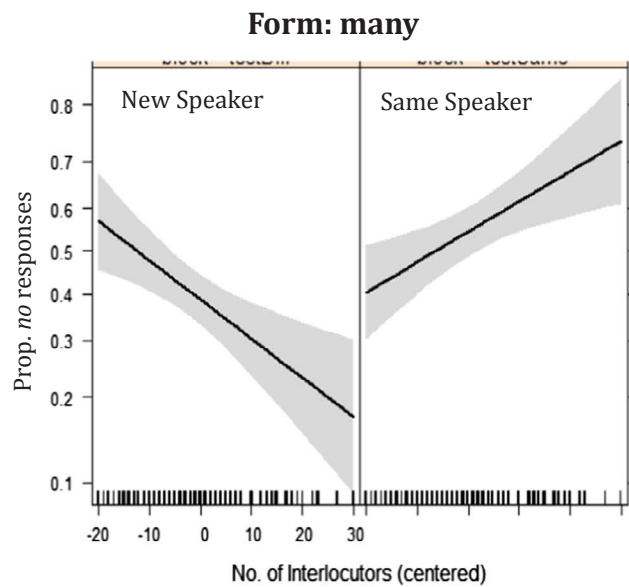## Appendix A. Full table of results of Experiment 1

Table of results of perception test phase

	β	SE	z	p-value
(intercept)	0.23	0.19	1.19	0.23
Network Size (centered)	0.02	0.02	1.30	0.19
Speaker (New)	−0.38	0.27	−1.39	0.16
No. of Hours (centered)	0.01	0.02	−0.69	0.49
No. of stars (centered)	−0.48	0.08	−5.84	5.25e−9
Network Size × Speaker	−0.05	0.02	−2.18	0.0295
No. of Hours × Speaker	−0.01	0.02	−0.33	0.74

Table of results of production test phase

	β	SE	z	p-value
(intercept)	8.01	1.18	6.76	1.4e−11
Network Size	−0.03	0.01	−2.06	< 0.04
No. of Hours	0.01	0.01	0.45	0.65
No. of stars	−0.60	0.09	−7.07	1.6e−12

Appendix B. Participants' responses in the prediction task broken down by form

Form: many

Form: some

Appendix C. Full table of results of Experiment 2

	β	SE	t
(intercept)	1.96	7.34e − 3	266.68
Time	1.90e − 2	1.78e − 4	106.60
No. Infected	− 3.85e − 4	6.50e − 5	− 5.92
Mutators' Network (Neighbors with Small Social Network)	− 6.49e − 2	6.94e − 3	− 9.36
Time × Mutators' Network	− 3.175e − 3	2.52e − 4	− 12.60

Appendix D. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.cognition.2018.03.003.

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