Language Change and Social Networks

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1. Introduction

• Social networks determining factor in languages

• Sociolinguistic studies of social networks focus on:
  ➢ Small communities
  ➢ Relation between individuals
  ➢ Example: three inner-city communities in Belfast
1. Introduction

- Multiple relationships within individuals
  - Relatives
  - Neighbors
  - Friends
  - Colleagues

- Different degrees of integration

- Linguistic behaviors related to integrity into network
  - The more integrated a person is, the more (s)he adapts to speech norms
1. Introduction

- Very few empirical data have actually been able to show the effect of social networks over a long time.

- It’s hardly possible to get the structure of large communities.
  - Can be done by computer simulations.

- Parameters can be manipulated due to computer simulations (population size, connectivity...).
1. Introduction

• BUT: Computer models cannot consider the actual population structure or *regular* or *random* networks.

![Social network diagram](image)

**Figure 1:** The social network in Nettle’s model of language change (1999). The numbers represent agents at different age stages. Nodes 1 and 2 represent infants and children, 3, 4 and 5 represent adults.
1. Introduction

- Recent studies show that large-scale networks (internet, friendship...) are not regular or random

- Two features discovered:
  - *Scale-free*
  - *Small-world*

Examination of the effect of social networks on the dynamics and outcome of language change
2. Language change as a diffusion process

- Language change = diffusion process of some new linguistic elements in language communities

- Language learner samples a (large) part of the language community in his peer group or older generations, NOT younger generations
  - New innovations unlikely learned by next generation: "Threshold Problem"
2. Language change as a diffusion process

• Overcoming the threshold:
  - Functional selection: a *functional bias* towards the innovation
  - Social selection: speakers with higher social impact favor the learning

• Model to study the threshold problem (by Nettle):
  - Simulation of attitude changes in social groups
  - Population structured in age and social status
  - Learner chooses one linguistic variant by evaluating their impact in the community
2. Language change as a diffusion process

- Model to study the threshold problem (by nettle):
  - Shorter social distance/higher social status $\Rightarrow$ stronger impact on learner
  - Innovation with small functional advantage has a high chance to spread
  - **Conclusion:** functional biases maybe affect the direction of language change, but may not provide the conditions for change
  - **Challenge to explain „changes from below“:** many changes start in upper working class or lower middle class
3. The model

- Population represented as network with $N$ nodes (agents)

- Two linguistic states
  - Unchanged form of innovation: $U$
  - Changed form of innovation: $C$

- Age structure from 1 (infants) to 5 (adults)

- 1+2 learners; 3–5 teachers
3. The model

- Old agents get replaced

- Illustration, how a learner might learn from neighbors:

\[
F(U) = fuqu \\
F(C) = fcqc
\]

- U and C in the input => learning form with higher fitness
3. The model

- Fitness measured by:
  - Function of incorporating the functional value \((\text{fu}/\text{fc})\)
  - Frequency in the learner’s neighborhood \((\text{qu}/\text{qc})\)

- State of the learner:
  
  \[
  S(L) = \begin{cases} 
  U & \text{if } F(U) > F(C), \\
  C & \text{if } F(U) \leq F(C). 
  \end{cases}
  \]

- Example:
  - Network of 10 agents
  - Learner connected with 4 agents, 3 use \(U\), 1 uses \(C\)
  - Functional values: \(U=1; \ C=4 \Rightarrow F(U)=3; F(C)=4\)
  - Learner will learn \(C\)-form
3. The model

• Example:
  - Assumption: \( fu = 1 \)
  - Using parameter functional bias \( \beta \), measuring functional advantage of \( C/U: \beta = fc/fu \)

• Diffusion process compared in 4 different kinds of network structures:
  - Random
  - Regular
  - Small–world
  - Scale–free
4. The effect of different types of networks

- The diffusion is successful in all types of networks, but the curves look different

Figure 2: Diffusion dynamics in four types of networks in 20 runs (x axis: the number of generations, y axis: the percentage of changed form used in the population) (population size N=500, average degree <k>=20, functional bias β=20, and number of innovators I=1). (a) regular network; (b) small-world network; (c) random network; (d) scale-free network.
4. The effect of different types of networks

- The diffusion rate in small-world networks now changed, because the number of short-cut relations are smaller.

Figure 3: Diffusion dynamics in four types of networks in 20 runs under another set of condition: N=500, \( \langle k \rangle = 20, \beta = 10, l = 10 \). (a) regular network; (b) small-world network; (c) random network; (d) scale-free network.
4. The effect of different types of networks

- Runs with unsuccessful diffusion

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**Figure 4:** Diffusion dynamics in four types of networks in 20 runs with a small functional bias ($\beta=2$) but a large number of innovators ($I=100$). (a) regular network; (b) small-world network; (c) random network; (d) scale-free network.
4. The effect of different types of networks

- Between 3 to 7 regular and small-world networks have a higher probability of diffusion rate than the others.
- Small-world and regular networks: high success probability, but slow diffusion rate.
- Random and scale-free networks: high diffusion rate, but no slow success probability.

Figure 5: (a) Probabilities of successful diffusion under different functional biases; (b) Average diffusion time over 100 runs ($N=400$, $<k>=20$, $l=10$).
5. Effect of two types of learners

- Learner learn from all connected neighbors at age stage 1+2

- Two types:
  - **Categorical**: adopts form with higher impact
  - **Probabilistic**: adopts both forms and uses them proportional to their impact

- Probabilistic learners make language change so frequent
5. Effect of two types of learners

- If the learners are all probabilistic diffusion is possible
- In small-world networks the rate is higher but it takes longer

Figure 6: The diffusion dynamics in a population with all probabilistic learners in two networks. \(N=500, \langle k \rangle=20, \beta=2, I=1\). (a) small-world network; (b) scale-free network.
5. Effect of two types of learners

- The more probabilistic learners there are, the faster diffusion there is.

Figure 7: Probability of successful diffusion in populations with different proportions of probabilistic learners, under different functional biases. (N=500, <k>=20, l=1). Upper panel: small-world network; lower panel: scale-free network.
6. Effect of different population size

Figure 8: The relation between population size and the rate of change in four types of networks (N=500, \( <k> = 20, l = 1, 50\% \) probabilistic learners). (a) regular network; (b) small-world network; (c) random network; (d) scale-free network.

Figure 9: The average path length with respect to different network sizes in the four types of networks.
7. Conclusion

- Regular and small-world networks: high success probability, but slow diffusion rate

- Random and scale-free networks: fast diffusion rate, but lower success probability

- This model shows that there is a very high probability of linguistic change as long as there is at least a small number of probabilistic learners
8. Personal statement

- I think the model is very abstract, because the study is based on a computer simulation not on real world community structures.

- I now know some models that may explain language innovations better.

- It is interesting that it depends on the type of learner if an innovation spreads.