From Linguistic Innovation in Blogs to Language Learning in Adults: What do Interaction Networks Tell us?

Michał B. PARADOWSKI[1], Chih-Chun CHEN[2], Agnieszka CIERPICH[1], Łukasz JONAK[3]

Abstract. Social networks have been found to play an increasing role in human behaviour and even the attainment of individuals. We present the results of two projects applying SNA to language phenomena. One involves exploring the social propagation of neologisms in a social software (microblogging service), the other investigating the impact of social network structure and peer interaction dynamics on second-language learning outcomes in the setting of naturally occurring face-to-face interaction. From local, low-level interactions between agents verbally communicating with one another we aim to describe the processes underlying the emergence of more global systemic order and dynamics, using the latest methods of complexity science.

In the former study, we demonstrate 1) the emergence of a linguistic norm, 2) that the general lexical innovativeness of Internet users scales not like a power law, but a unimodal, 3) that the exposure thresholds necessary for a user to adopt new lexemes from his/her neighbours concentrate at low values, suggesting that—at least in low-stakes scenarios—people are more susceptible to social influence than may erstwhile have been expected, and 4) that, contrary to common expectations, the most popular tags are characterised by high adoption thresholds. In the latter, we find 1) that the best predictor of performance is reciprocal interactions between individuals in the language being acquired, 2) that outgoing interactions in the acquired language are a better predictor than incoming interactions, and 3) not surprisingly, a clear negative relationship between performance and the intensity of interactions with same-native-language speakers. We also compare models where social interactions are weighted by homophily with those that treat them as orthogonal to each other.

1 LANGUAGE PHENOMENA EXHIBITING COMPLEX SYSTEM CHARACTERISTICS

Within an individual, many linguistic mechanisms are at work, such as the perceptual dynamics and categorisation in speech, the emergence of phonological templates, or word and sentence processing. There are also a multitude of interactions simultaneously occurring at the society level between systems that are inherently complex in their own right, such as variations and typology, the rise of new grammatical constructions, semantic bleaching, language evolution in general, and the spread and competition of both individual expressions, and entire languages. Nearly two hundred papers have already been published dealing with language simulations. However, many of them, devoted to phenomena such as language evolution, language competition, language spread, and semiotic dynamics, were based on regular-lattice *in silico* experiments and as such are grossly inadequate, especially in the context of the 21st c. The models:

- only allow for Euclidean relationships (while nowadays more and more of our linguistic input covers immense distances; spatial proximity ≠ social proximity),
- are 'static' (while mobility is not exclusively a 20th or 21st-c. phenomenon, as evidenced by warriors, refugees, missionaries, or tradespeople),
- assume an identical number of 'neighbours' for every agent (4⊻8),
- presuppose identical perception of a given individual's prestige by each of its neighbours[4], as well as
- invariant intensity of interactions between different agents,
- most fail to take into account multilingual agents[5],
- have no memory effect, and
- zero noise (while noise may be a mechanism for pattern change).

To address these limitations, rather than take a modelling outlook, we can start with analysing language phenomena in social networks—either by tapping into already available repositories of data nearly perfectly suited to large-scale dynamic linguistic analyses, such as the Internet, or by analysing communities of speakers via offline approaches—and subsequently applying SNA and other complexity science tools to the analyses. Roman Jakobson remarked already half a century ago on the "striking coincidences and convergences between the latest stages of linguistic analysis and the approach to language in the mathematical theory of communication" ([17] p. 570).[6]

[1] Inst. of Applied Linguistics, Univ. of Warsaw, ul. Browarna 8/10, 00-311 Warsaw, Poland. Email: michal.paradowski@uw.edu.pl; a.cierpich@student.uw.edu.pl.
[2] Centre d'analyse et de mathématique sociales – UMR 8557, École des hautes études en sciences sociales, 190-198, avenue de France, 75244 Paris cedex 13, France. Email: c.chen@abmcet.net.
[3] National Library of Poland, Al. Niepodległości 213, 02-086 Warsaw, Poland. Email: lukasz@jonak.info.

[4] But see e.g. [13] or [33] incorporating complex network architectures and differences in prestige.
[5] But see e.g. [2].
[6] « Il est un fait que les coïncidences, les convergences, sont frappantes, entre les étapes les plus récentes de l'analyse linguistique

2 LANGUAGE ON THE INTERNET

Erstwhile research on language evolution and change focused on large time-scales, typically spanning at least several decades. Nowadays, observable changes are taking place much faster. According to [12] a new English word is born roughly every 98 minutes (admittedly an overrated estimate owing to methodological problems). Particularly useful for multi-angle analyses of language phenomena are Web 2.0 services, with content (co)generated by the users, especially the ones which allow enriching analyses with information concerning the structure of the connections and interactions between the participating users. This unprecedented reliance on news delivered by the users is also increasingly being observed in editorial offices and television newsrooms.

The uptake of novel linguistic creations in the Internet has been commonly believed to reflect the focus of attention in contemporary public discourse (suffice it to recollect the dynamics and main themes of status updates on Twitter following the presidential elections in Iran, Michael Jackson's death, Vancouver Olympic Games, and the recent Oscar gala, last July's L.A. earthquake, the Jasmine Revolution—by some also called the "Internet Revolution"—in Tunisia, the developments in Libya, the 2011 Tōhoku earthquake and tsunami, or ibn Laden's death, see e.g. [11]). However, even where the topics coincide, the proportions in the respective channels of information are divergently different (correlation at a level of a mere .3; e.g. [27], just as television ratings cannot be used to predict online mentions; [26]), just as not infrequently the top stories in the mainstream press are markedly different than those leading on social media platforms (e.g. [29]). The emotive content of comments on different social platforms is also distinctly different ([5], [6]).

Table 1. The microblogging site in numbers (at time of data dump)

Users	20k, over half logging on daily
Users in the giant component	5.5k (density 0.003)
Relations	110k
Tags[7]	38k
Tagged statuses	720k

While there does exist some scarce research looking at the emergence and spread of online innovation[8], studies that do so utilising social network data are next to non-existent. Our empirical research project has set out to investigate how mutual communication between Internet users impact the social diffusion of neological tags (semantic shortcuts) in Polish microblogging site Blip (for site statistics, see Table 1).

et le mode d'approche du langage qui caractérise la théorie mathématique de la communication. » (*Essais de linguistique générale*, 1967:87)

[7] By tags (or 'hashtags') we mean expressions prefixed with the number sign '#' and usually used in microblogging sites to mark the message as relevant to a particular topic of interest, or 'channel'.

[8] *Cf.* e.g. [24] for how the use of Internet chatrooms by teenagers is resulting in linguistic innovation within that channel of virtual communication, [18] for a discourse-analytic glance at the social practices of propagating online memes, or [22] for a visualisation of the 'competition' between top quotes in the news during the 2008 US presidential election.

3 TAGS AND SOCIAL COORDINATION

The intended purpose of tagging systems introduced to various Web 2.0 services was to provide ways of building *ad hoc*, bottom-up, user-generated thematic classifications (or "folksonomies"; [35]) of the content produced or published within those systems.

However, the tagging system of Blip became much more than that, as users redefined the meaning and modes of using tags. In the site, tagging is not merely a mechanism for retrospective content classification, but also provides institutional scaffold for on-going communication within the system. From the point of view of *individuals*, using a tag within a status update still provides information about what the update is about, but also implies joining the conversation defined by the tag, and, consequently, subscribing to the rules and conventions governing conversation. In this sense, the system of tags can be thought of as an institution (as sociologically understood), regulating and coordinating social conduct – here, mostly communication. From the *systemic* point of view, tags-institutions define what Blip.pl is about, the meaning of its dynamics, and its culture.

4 THE LONG TAIL OF THE BLIP CULTURE

One of the preliminary results obtained from the data analysis carried out concerns tag popularity, whose distribution scales like a power law (Fig. 1), a feature Blip shares with a wide range of natural, technological and socio-cultural phenomena (*cf.* e.g. [3], [25]). Our assumption is that at least a considerable proportion of popular Blip tags constitute the "meaning" and structure of the system, its cultural and institutional establishment, while the long tail consists of more or less contingent representations. Our interests lie in answering questions about the mechanisms which were responsible for the system becoming the way it is in terms of cultural tag composition.

Figure 1. Tag popularity distribution in Blip

5 SOCIAL INFLUENCE AND DIFFUSION

The most important mechanism we are looking for has to do with diffusion of innovation. Diffusion and creation of novelty has been traditionally assumed to be among the most important social processes [7]. In our case, each of Blip's tags, a potential communication coordinator, had been first created by a user, then spread throughout the system with greater or smaller success (see Fig. 2). Some of the most successful, most frequently imitated tags have become Blip's culture and structure.

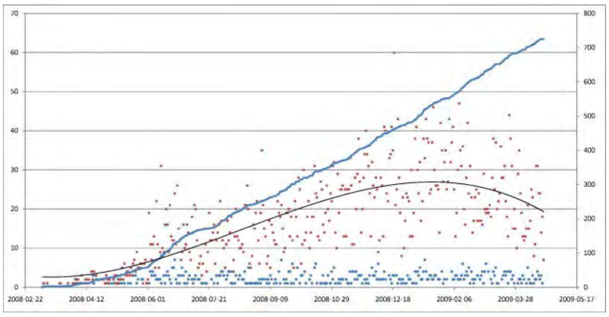

Figure 2. Evolution of the popularity of an idiosyncratic tag, relative to system size; abscissæ: time, ordinates left: percentage of saturation; ordinates right: absolute count; blue rhomb dots: first usages; red square dots: subsequent usages; thin black line: subsequent usage trend (multinomial); thick blue line: first usages cumulative

There are a number of theories explaining the mechanisms of diffusion of novelty, and one of our goals is to find out which best accounts for our data. Memetic theory assumes that ideas (here coded as words-tags) are like viruses which "use" the mechanisms of the human mind to reproduce. The most successful reproducers would be those optimally adapted to the environment of the mind – its natural dispositions and the ecosystem of already established ideas ([4], [8]).

The theory of social influence constructs a situation in which individual behaviour (including adoption of innovation) is contingent on peer pressure. The threshold model of collective behaviour postulates that a person will adopt a given behaviour only after a certain proportion of the people s/he observes have already done the same. This proportion—the "adoption threshold"—constitutes the individual characteristic of each member of the group ([14], [34]).

A third point of view is offered by the social learning theory [1], which assumes that innovation or behaviour adoption is a result of a psycho-cognitive process which involves evaluation of other people's behaviour and its consequences. In this case the adoption process is perceived as more reflexive and less automatic than the previous two ([15], [30]).

The preliminary analysis conducted involved calculating thresholds for all tag adoptions (i.e., their *first* usages). We describe the user-tag network with a bipartite graph $G = G(U,X,E)$, where U is the set of users, X is the set of tags, and E represents the edges between users and tags. The user-user network we define using a directed graph $D = D(U,H)$, where H is the set of edges. To every $e_{u\to x} \in E$ edge connecting user u to tag x added in time $\tau_{u\to x}$ we assign a variable $a(e_{u\to x})$, such that

$$a(e_{u\to x})\begin{cases} 1 \text{ if in time } \tau_{u\to x} \text{ there is a neighbour of } u \text{ who is} \\ \text{already connected to tag } x, \\ 0 \text{ else} \end{cases}$$

We capture the adaptive behaviour of a user with the statistical variable $\alpha_u \in \langle 0,1\rangle$

$$\alpha_u = \frac{\sum_{e_{u\to x}\in E(u)} a(e_{u\to x})}{|E(u)|}$$

where $E(u) \in E$ is the set of connections of user u. A low value of α_u means that the user tends to introduce more innovation into the system.[9]

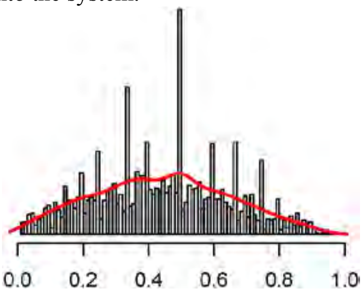

Figure 3. Creativity distribution in the microblogging site

Using the above notation, β_u is the (mean) measure of the number of alters (neighbours == followed users in Twitter/Blip terms) who had adopted a given tag before user u. We only consider first usages:

$$\beta_u = \frac{\sum_{e_{u\to x}\in E(u)} \frac{A_{(e_{u\to x})}}{H_{(t)}(u)}}{|E(u)|}$$

where:

- $A(e_{u\to xt})$ is the number of neighbours of u who are already connected to x at time $\tau_{u\to x}$ (in other words, it says how 'mainstream' the tag is);
- $H_{(t)}(u)$ is the number of neighbours of u at time t;
- $E(u)$ is the total number of (unique) tags used by u.

Thus, a high value of β_u corresponds to the user being more likely to be influenced by his/her neighbours.[10]

The resultant distribution of the thresholds is considerably skewed, with a median of 0.11 and a long tail of higher values (Fig. 4)[11]. This suggests that the population of Blip users is generally innovative and/or corroborates the viral model of diffusion over the two alternative theories mentioned above. However, we expect other factors (such as tag and user characteristics) to play an important role as well, especially since, contrary to many common expectations, expressions' popularity correlates negatively with low thresholds (Fig. 5).

An alternative explanation may be the classical diffusion process with population division into early adopters and laggards: thresholds rise with tags' popularity because users with lower thresholds had adopted them earlier (when the expressions were not yet popular). Our aim is to consider models that include these factors in explaining diffusion

[9] Although a large alpha can also be observed in cases where a user is surrounded by many neighbours who adopted a tag before her/him. Naturally, given the nature of the data recorded by social software, it is impossible to determine which entries a given user has actually read. This of course means that the posts published by 'followed' persons are merely treated as a realistic proxy of the data actually seen by the user.

[10] A thematic breakdown of the tags might reveal that humans succumb to influence more easily in certain contexts than others.

[11] The "humped" feature of the distribution tail stems from the skewed distribution of the variables used to calculate the threshold values.

mechanisms.

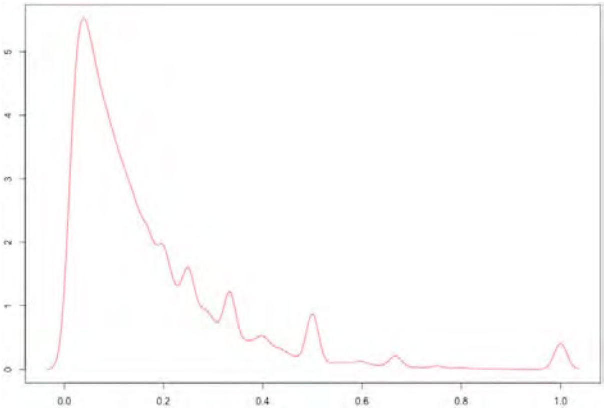

Figure 4. Distribution of tag adoption thresholds in Blip

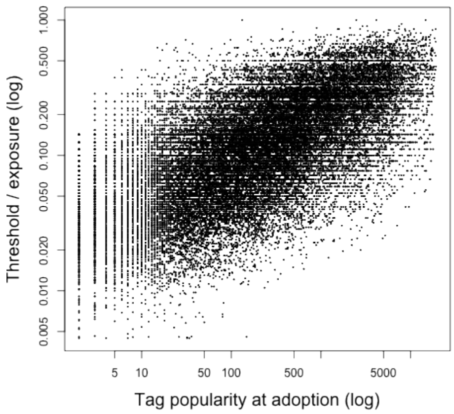

Figure 5. Relationship between tag popularity and exposure threshold

6 FOREIGN LANGUAGE STUDIES AND SOCIAL INTERACTION

In the field of foreign language studies, the past two decades have witnessed a significant increase in theories and research focused on the role of social interaction (e.g. socio-cultural theory [20], language socialisation hypothesis [19], or conversation analysis [9], [10]). These developments conceive of language learning as a process anchored in and configured through the activities in which the language user engages as a social agent [28]. Yet, to date no data-driven analysis has been carried out to investigate the impact of social network structure and peer interaction dynamics on second-language learning outcomes in the setting of naturally occurring face-to-face interaction.

7 SECOND LANGUAGE ACQUISITION AND LANGUAGE LEARNER NETWORKS: PARTICIPANTS, METHODS & MEASURES

During the 2010/11 academic year, a striking observation was made independently by several German-language instructors at one university in Baden-Württemberg: for the first time in a long while the cohort of Erasmus exchange students arriving at the university became a visibly cohesive group. This had a measurable impact on the improvement of their linguistic competence over the course of the academic year.

All members of the group (n=39) were approached with in-depth structured interviews, with the objective to grasp: (i) the precise individual, social and interactional factors impacting the acquisition process; (ii) the way in which language development is affected by the dynamics of peer interaction, and (iii) the impact of social network topology on motivation and learning outcomes. From these interviews, we were able to gain insight into the motivations, preferences and peer interaction among the participants. The goal was then to determine how, if at all, these were associated with performance. Because the number of participants was very low and the majority improved by one level, we chose to focus on over- and underperformers (improvement by two levels or no improvement) to try to identify the features and conditions that might explain their outcomes.

We measured *performance* in terms of self-reported improvement, taking the difference between the participant's initial level in German and their level at the end of the course.

Interaction frequency was assessed by the participants themselves and rated on a scale between 1 and 10, where a score of 10 was given for participants with which the individual felt s/he interacted most frequently.

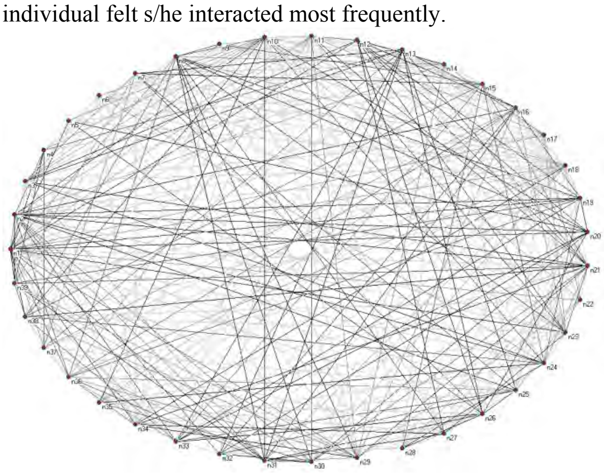

Figure 6. Bidirectional interactions in German; edge intensity indicates relative link weight

In our analyses, we consider eight different weighted interaction networks, namely those of: (i) incoming interactions, where an individual i has an in-link from individual j if j has reported interacting with i (irrespective of whether or not i has reported such interaction); (ii) outgoing interactions, where individual i has an out-link to an individual j if i has reported interacting with j; (iii) the sum of general interactions; (iv) bidirectional interactions only; (v) incoming interactions *in German*; (vi) outgoing interactions *in German*; (vii) the sum of *German* interactions; (viii) bidirectional interactions *in German* (a snapshot of the last network is visible in Fig. 6).

The interactions were all normalised with respect to participants' general interactions (so, for example, if a participant had a high level of interaction, a score of 4 will be treated the same as a score of 2 for a participant who did not interact very much).

Due to the low number of participants and the fact that the majority improved by one level, we had to ensure that any apparent similarities between strongly linked individuals (large frequencies of interactions) were not simply due to homogeneity. To address this, we compared the predictions that would be made by the network with those that would be made by the network randomly rewired. Rather than use traditional network analysis methods that depend on large numbers of nodes and links, we tested hypotheses by evaluating alternative models that overlay or weight networks. For example, to gain further insight on the interplay between social factors, language factors, and homophily ([21], [23]), we compare models where social interactions are weighted by homophily with those that treat them as orthogonal to each other.

8 SOCIAL INTERACTION AND PERFORMANCE

Using this multi-layered-network perspective to study socially distributed learning, we found:

(i) No direct association between outgoing interactions (neither general nor in German) and performance. However, when the outgoing *German* interactions were framed in the context of the *general* outward interactions (i.e., using $\frac{s_{german}}{s_{general}}$, indicating the degree to which they interacted in German less or more when compared with their general interactions), there appeared to be a positive association (see Fig. 7);

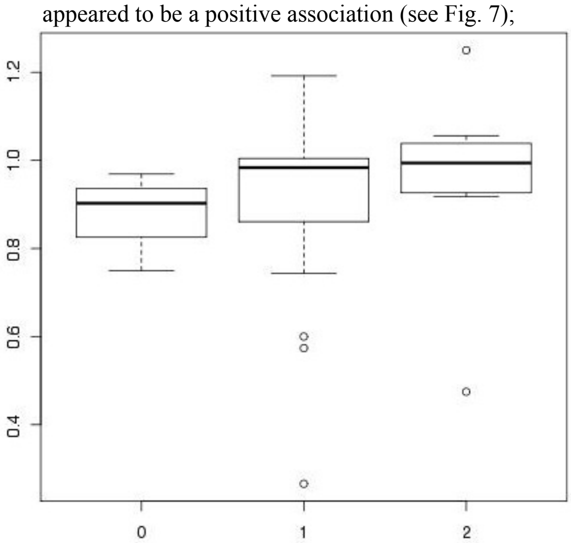

Figure 7. Boxplot of normalised sociability in German (outward interactions) and improvement by levels

(ii) Participants who did not show improvement had fewer general incoming interactions, but more German incoming interactions. The latter effect is even more prominent when framed in the context of the former. This finding may first seem counterintuitive (suggesting that more incoming German interactions are associated with poorer performance). However, if we remember the fact that for each participant, incoming interaction scores are dependent on the reports of *other*, it follows that those receiving more incoming interactions are at the same time enabling others to have more outgoing interactions (in other words, they are being 'used' by others for speaking German; *cf.* Fig. 8);

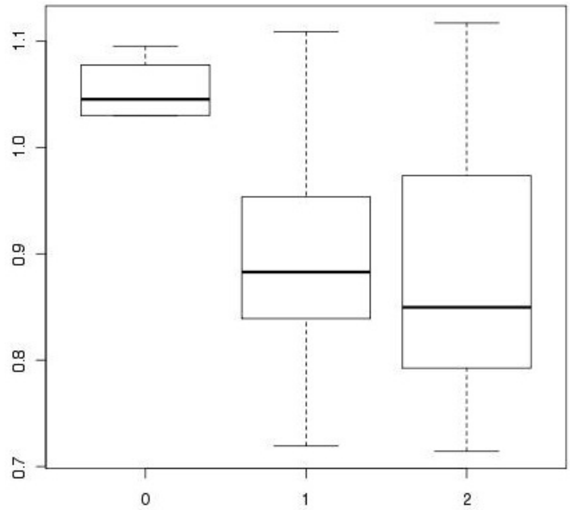

Figure 8. Boxplot of normalised popularity in German (incoming interactions) and improvement by levels

(iii) Neither incoming nor outgoing *German* interactions alone are strongly associated with homophily in performance. However, when both are considered, the frequency of interaction between participants is strongly associated with similarity in their performance;

(iv) There appeared to be no relationship between *general* interactions and performance;

(v) There was a clear negative relationship between performance and the number of interactions with participants with the same native language such that participants who showed no improvement in level interacted significantly more with those sharing their native language than did the participants who improved by two levels. This effect was observed both for the general and the German interactions:

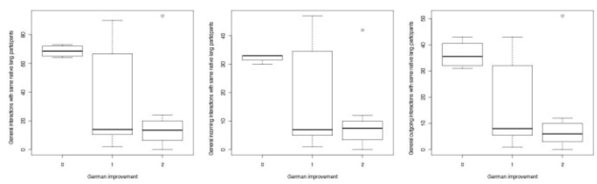

Figure 9. Boxplots of general interactions with same-native-language participants. Left: both incoming and outgoing, Centre: incoming, Right: outgoing

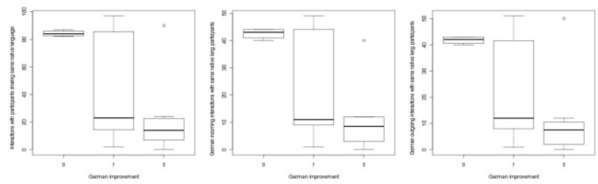

Figure 10. Boxplots of German interactions with same-native-language participants. Left: both incoming and outgoing, Centre: incoming, Right: outgoing

9 CONCLUSIONS

The results of social network analyses not only help understand social behaviour and determine the degree to which individual agents succeed in achieving their goals, but also provide useful indications for systems where non-human agents have to interact or teamwork with other artificial or human actors, machine learning and collective intelligence. The design of intelligent machines would benefit from seeing them as actors in a realistic social context, where the number, nature and influence of neighbours play an important part in the learning process. For instance, exposure thresholds and creativity ratios can constitute useful benchmarks for machines learning from and interacting with many other agents, while the finding that outgoing interactions in the acquired language are a better predictor of performance than incoming interactions support Swain's Output Hypothesis [32] and the emergent grammar theory [16] lying behind formalisms such as Fluid Construction Grammar [31], which is used in robotics.

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