_lognostics
tools for vocabulary research

Simulating word associations in an L2: the effects of structural complexity.

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1: Introduction

This paper is the third of a series of studies in which we have used simulations of word association behaviour as a way of investigating how L2 mental lexicons are organised. In the first paper in this series (Wilks & Meara, 2002), we reported data from an experiment in which we tested the ability of L1_English speakers to recognise associated pairs in small sets of French words, (the *five-word task*). The material used consisted of a 40 item questionnaire. Each item in the questionnaire comprised a set of five words randomly chosen from the *Français Fondamental* list: approximately the first thousand most frequent words in French excluding grammatical items (Gougenheim et al. 1956). The participants were instructed to read each set of words and circle any two words in the set that they considered to be associated. A typical item might look like example one below:

Ex. 1 blouse cheminée coûter feu tort

In example 1, we would expect good speakers of French to circle *cheminée* (chimney) and *feu* (fire). If the participants saw more than one pair of associated words in the set, they were instructed to circle only the two words with the strongest link. If they found no links between any of the words they were instructed to write nothing, and continue to the next item.

Alongside this group of L1_English speakers, we also ran a group of L1_French speakers, who carried out the same task. Our intention was to compare the data of the L1_English speakers with the native speakers of French, and we expected, of course, to find that our L1_English speakers were less adept at identifying associated pairs than the L1_ French speakers were. Not surprisingly, this turned out to be the case ($t=6.47$, $p<.001$). The data we reported are presented in table one below.

Table 1: Mean hit rate per group

	Nonnative Speakers	Native Speakers
Mean hits	19.00	30.90
Standard Deviation	7.65	5.74
number of items	40	40
number of Ss	30	30

These data clearly confirm that there is a difference between the two subject groups, and in our original paper, we argued that the most obvious explanation of this difference is that the association network of the L1_group is "denser" than that of the L2_group. The idea here is that L1 words have more associative connections than L2 words do, and that the number of connections directly affects the likelihood of Ss finding a pair of associated words in each stimulus set. We pointed out in Wilks and Meara (2002) that this density metaphor is one that frequently occurs in the literature on L2 word associations, but its implications are rarely developed. Aitchison (1987), for example, talks about the lexicon as "a gigantic multidimensional cobweb", while for Bogaards (1994), "… le lexique évoque l'image des toiles d'araignée qui flottent au vent. Les matériaux lexicaux se présentent dans des structure ultra-légères qui s'adaptent avec une souplesse et une flexibilité incroyables…" . Similar descriptions can easily be found in other widely-read authors, and most researchers in fact appear content to operate on this descriptive level. Wilks and Meara, however, attempted to show that it was possible to move beyond these imprecise metaphorical descriptions, and develop more specific quantitative models instead. We did this by comparing the experimental data with data generated by an association simulator.

The simulator was a computer program that modelled a small, 1000-word lexicon in which each word was linked with a number of other words in the lexicon. The number of links between each word and the rest of lexicon - the NLinks parameter - could be varied, and Wilks and Meara showed that the probability of two associated words appearing in a small set of words varied with the value of this parameter. We then used this data to look again at the data generated by real subjects, and estimated what the real data implied about the density of interword connections in the mental lexicons of our test takers. Our initial guess had been that the L1_English speakers would have relatively few connections between words in their L2 lexicons, perhaps as few as four or five. However, the results generated by the simulator forced us to revise that estimate. We concluded that the data implied a much denser set of connections, even for L2 speakers, perhaps as many as 30 or 40 links for each word. Our 2002 paper considered the implications of this for the way we normally interpret word association data generated by L2 speakers, and we concluded that the density of connections between words would have to be considerably higher than most researchers assumed it to be. This had significant implications for the way we thought about word association networks in an L2.

2: Earlier Simulations

In our original paper, the simulator that we worked with consisted not of real words, but of a large array of numbers, which we considered to be the equivalent of "words" in a real lexicon. Our model lexicon consisted of 1000 "words": each word was linked randomly to a number of other words, which we consider to be associates of the original word. The overall structure of our model lexicon looks something like table 2.

Table 2: part of a simulated lexicon where each "word" is randomly associated with a number of other "words".

word 1	123	145	160
word 2	99	182	279
word 3	129	182	761
...			
word 999	135	856	687
word 1000	72	65	321

Here, each word is associated with three other words: word 1 is associated with word 123, word 145 and word 160; word 2 is associated with word 99, word 182, and word 279; and so on. In a simulation, it is a straightforward matter to vary the number of association links: the number of associations appears as a parameter in the model, and developing a model with four, five, six or more associates for each word is merely a matter of changing the value of this parameter, and setting up a new model with the relevant new parameter.

In each trial of the simulator, the program mirrored our original study by randomly selecting a set of five stimulus words, and looking for an associational link between them. An example of a trial of this sort is shown in Table 3. The table contains a set of five stimulus words word29, word367, word456, word552 and word669 - each of which is associated with six other words.

Table 3: a simulated trial

word 29	15	123	135	138	742	881
word 367	29	421	435	567	665	678
word 456	71	138	156	489	543	820
word 552	81	140	172	495	681	729
word 699	10	259	273	682	695	891

In our original paper, we programmed the simulator to register a hit if one of the five stimulus words also appeared in the association list of one of the other stimulus words. In Table 3, for example, word 29 occurs in the association list of word 367, and the program would therefore register a hit for this trial. By running lots of trials, typically a thousand, it is relatively straightforward to estimate the probability of at least one hit being registered for a random set of five target words.

However, a number of critics argued that our method of determining a hit in these simulations was a very conservative one, and they made a very good case for adopting a different approach, arguing that alternative definitions of a hit were more plausible than the one we had adopted. For example, in Table 3, word 138 appears as an associate of both word 29 and word 456, and we might want to argue that these two stimulus words are linked by this common associate. If word 29 were BIRD, word 456 were ROCKET, and word 138 were FLY, it would be plausible to argue that BIRD and ROCKET might be identified as associates, even though neither appears in associate list of the other. In the second paper in this series, Wilks, Meara and Wolter (2005), therefore, we examined the extent to which the results of a simulation could be affected by different ways of identifying a "hit" in the five-word task.

It is obvious with hindsight that adopting a more lenient approach to identifying a hit in a set of stimulus words will have a dramatic impact on the likelihood of a hit being registered. Wilks, Meara and Wolter (2005) examined four different ways of identifying a hit, and concluded that more lenient methods of identifying a hit had significant consequences for identifying systematic differences between L2 speakers and native speakers. In these models, the probability of registering a hit for a set of five target words was surprisingly high, even when the number of associates for each word was fairly small. Wilks, Meara and Wolter concluded, somewhat pessimistically, that it might be extremely difficult to move from raw data like the data reported in Wilks and Meara's original experiments, to more general theoretical claims about the way L2 lexicons grow in complexity.

3: Modelling Lexical Structure

In this paper, I will consider a second set of problems which arose in the discussion of our original paper. One of the main objections which appeared in these discussions concerned the way we had operationalised the structure of the lexicon itself. In the work described in Wilks and Meara (2002) and Wilks, Meara and Wolter (2005), we had modelled our lexicons using random associations between words. Each word was randomly connected to N other words, selected by chance, but the number of associations was the same for each word. This introduced a level of uniformity into our models which is probably not characteristic of real lexicons. Real lexicons, it might be argued, are not likely to be ordered in this way. Specifically, we could argue that the number of associations linked to each word is not likely to be uniform, and probably varies quite a lot. Further, we could argue that the associations made between words are not likely to be random. At the very least, some words are more likely to be involved in an association link than others are, and we need to find a way of reflecting this in our simulations. Finally, a number of people suggested to us that we needed to look at small world lexicons (Watts and Strogatz 1998, Ferrer i Cancho and Solé 2001, Watts 2003) in which a few densely structured associative clusters are connected by a small number of long-range associations between the clusters.

These ideas are explored in the rest of this section. In the simulations reported in this paper, I have set aside the question of how we decide whether an association among the five stimulus words is identified. In order to simplify things, I have only used the second procedure developed in Wilks, Meara and Wolter (2002). This is the model in which a set of stimulus words generates a hit whenever one of the stimulus words occurs as an associate of one of the other stimulus words, **or** any two of the stimulus words share a common association. This implementation is not the most generous of the models discussed in Wilks, Meara and Wolter, but it is considerably less conservative than their original model, and it is probably a good approximation of how people make associations in real life. It is possible that the variations on lexical structure modelled in this paper may in fact interact in complex ways with the method we use to determine whether a stimulus set contains a hit or not. This problem will not be discussed here, however, as the arguments are sufficiently complex already.

3.1 variable random models

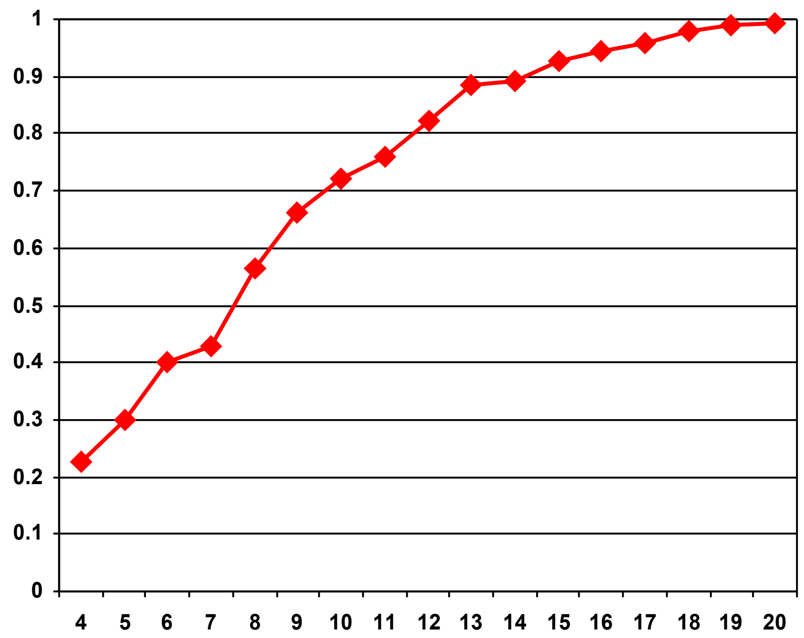
Figure 1 and Figure 2 show the effect of allowing the number of associations linked with each word in the lexicon to vary. Figure 1 recaps the data presented in Wilks and Meara (2002). It shows the probability of a hit being returned for a set of five randomly selected target words, when all the words in model have the same number of associations, and this figure is allowed to vary from 4 to 20. Figure two reports data from a set of simulations in which a slightly different approach is used. In these simulations, the total number of associational links in the model lexicon is determined, but these links are randomly distributed across the entire lexicon The number of associations any single word can have is not predetermined, and there is no limit on the number of associations any one word can have. In spite of this change of approach, the data reported in figure 2 are for all intents and purposes identical to the more constrained data reported in figure 1. This suggests that the over-riding factor that determines the probability of a hit being registered in a small stimulus set is the total number of associations in the lexicon, rather than the number of associations linked to any one word. As we shall see, this change of focus from the individual word to the total number of connections in the network turns out to be more interesting than it looks at first glimpse.

This general conclusion that the main factor affecting the occurrence of a “hit” is the total number of associational connections in the model lexicon is also reinforced by data from two further models. Figure 3 shows data from a set of simulations in which the number of associations per word parameter is treated as a maximum, rather than a fixed value. This allows the number of associations that any one word has to vary between zero and the maximum value defined by the parameter. In practice, this means that the average number of associations is about half the maximum, with a relatively wide standard deviation. This arrangement is illustrated in Table 3. Here, the maximum number of associations is six. The individual words vary from zero to six associations, and the average number of associations for the five words shown is three.

Table 3: a model lexicon where the number of associations is variable up to a maximum.

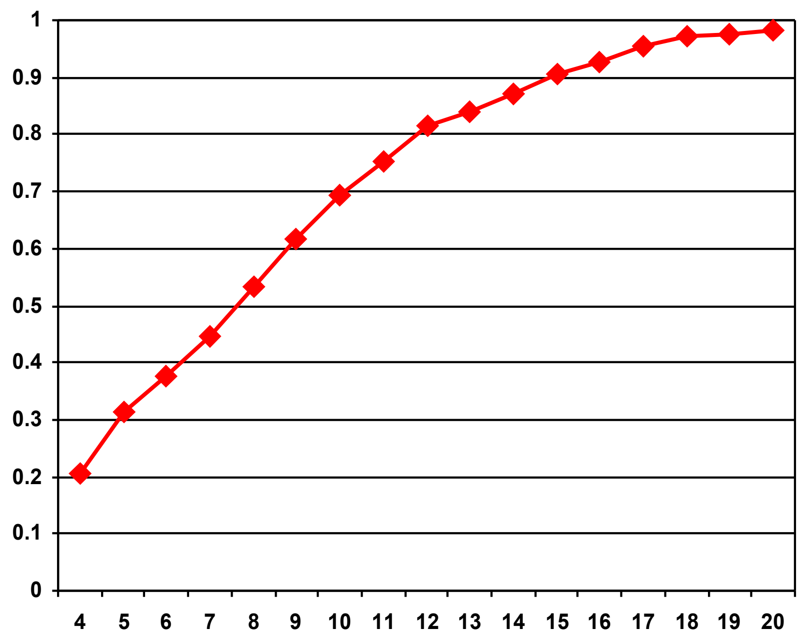
word 0001	0194	0456	0341	0222		
word 0002	0033	0006	0519	0343	0931	0945
word 0003						
…						
word 0999	0438	0456				
word 1000	0229	0179	0202			

Figure 1: Random Links Fixed N



number of associations for each word

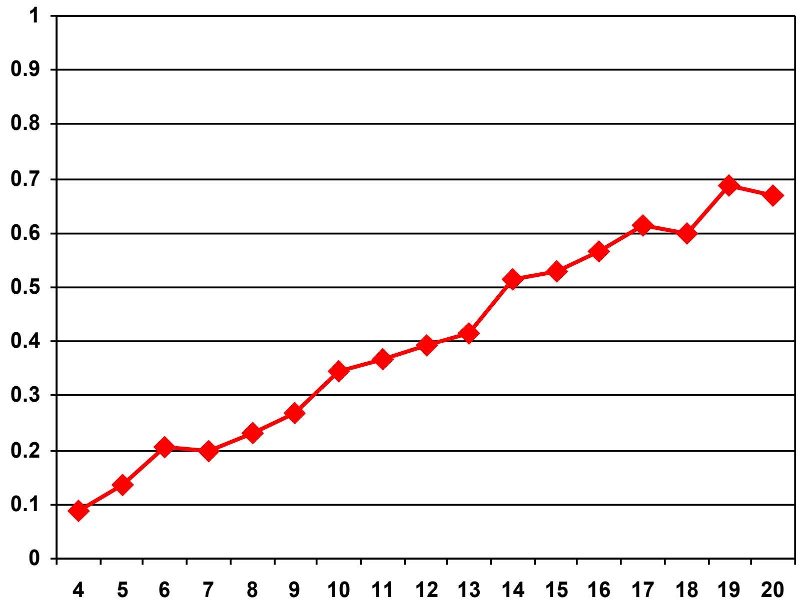
Figure 2: Random Links variable N



total associations in the network (000s)

At first sight, the data line in figure 3 looks rather different from the data reported in figure 1, but it is, in fact just a stretched out version of the same basic pattern. When the maxlinks parameter is set at 20, the average number of links per word is about 10, and in a model containing 1000 words, this means that the total number of associational links is about 10,000. The probability of registering a hit when the maxlinks parameter is set to 20 - .68 - is almost identical to the value of .69 that we found in the previous model when we had a total of 10,000 associational links in the model. Similarly, when the maxlinks parameter is set at 8, the average number of links per word is about 4, and the total number of links in the network is around 4000. The probability of registering a hit when the maxlinks parameter is set to 8 should therefore be around 0.2 - the value returned when the number of fixed links equals 4 in figure 1. And indeed this turns out to be the case.

Figure 3: Max Links = N



maximum number of associates for each word

A very similar data pattern also emerges if we allow the number of association links for each word to vary, but impose a relatively tight constrain on the amount of variation allowed.. The data in figure 4 shows what happens when the number of associations linked to each word is allowed to vary by plus or minus three. Thus, when the average number of links is ten, some words may have as few as seven links, while others may have as many as thirteen. Over a large lexicon, the number of association links in the whole lexicon is approximately the same as the number we get with a fixed number of links, and once again, we find that the data in figure 4 is almost identical to the data reported in Figure 1 and Figure 2.

Figure 4: Mean links = N

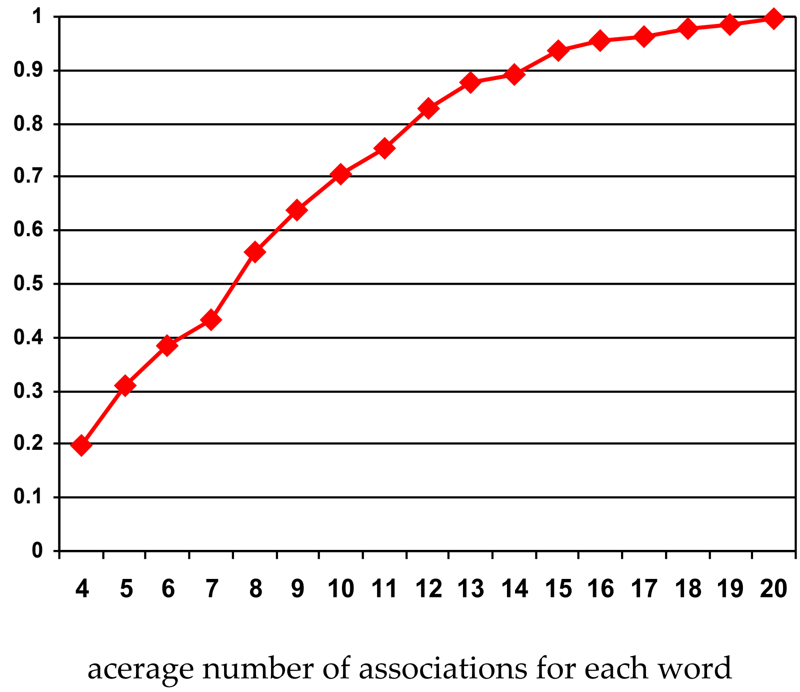
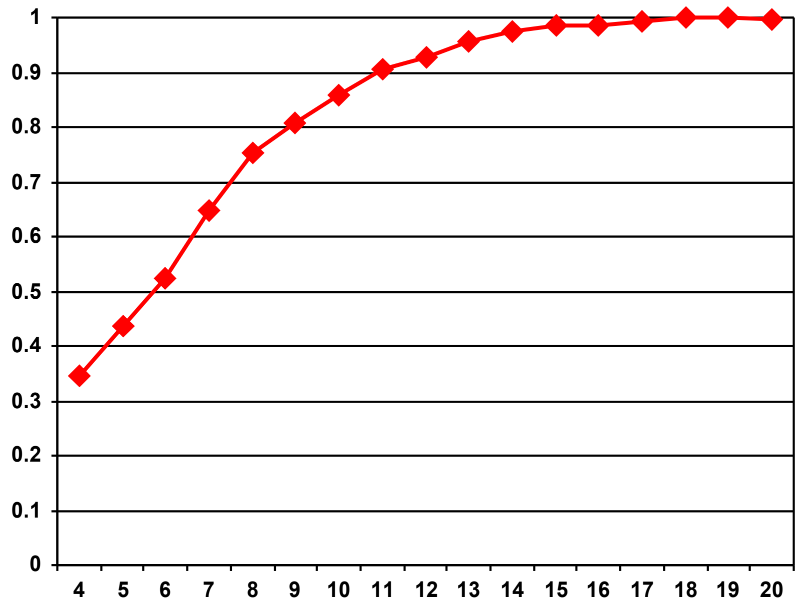


Figure 5 illustrates a slightly more complicated way of constraining the associational links between words. In this set of simulations, we have imposed the constraint that associations take into account the order in which words are acquired. The constraint applied here is that association links are normally allowed only with a word that appears earlier in the dictionary. That is, word 300 can associate with any earlier word (wds 1-299), but its association list cannot contain words which occur latter in the dictionary (wds 301-1000). This constraint, has the effect of giving more weight to words which appear early in the dictionary list, so that word 20, for example, is more likely to appear as an associate than word 920. In this way, the model loosely reflects what might happen in lexicon where developmental processes are a dominant factor.

Obviously, we cannot apply this constraint to all words: if we did, then word 0001 would have no words that it could associate to, word 0002 would only be able to associate to word 0001, and so on. Therefore, in the simulations reported in Figure 5, the first 50 words are allowed to associate freely with each other. This gives us a small core of fifty words which are highly interconnected and a large number of other words which are loosely connected to this central core. The choice of 50 words for this central core is an arbitrary one, but as far as I can see, other values for the size of the core work in essentially the same way.

Again, rather surprisingly perhaps, the results of these simulations look broadly similar to the random data reported in figure 1. The probability of a hit being registered in figure 5 is generally slightly higher than the probabilities reported in figure 1. This reflects the fact

Figure 5: a central core and ordered links.



Number of associations for each word.

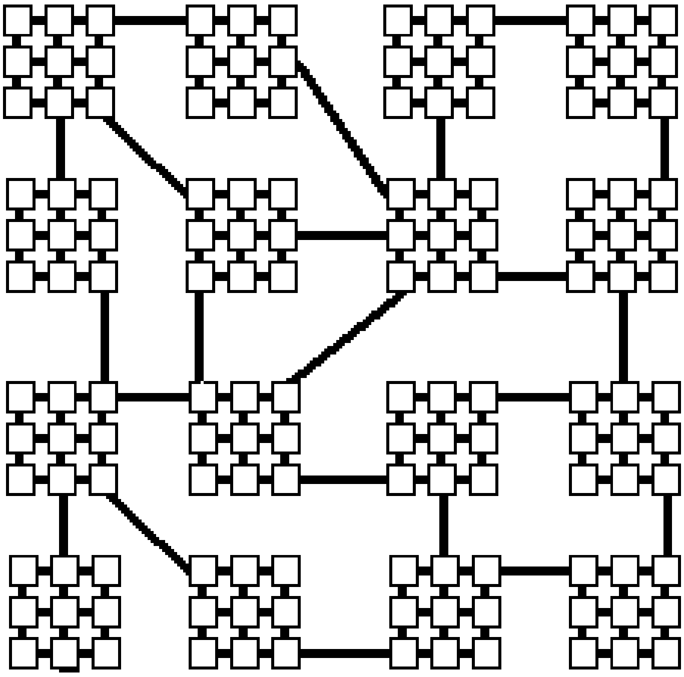
that in this model, the probability of a word appearing in a list of associates is not equal for all words: words that appear early in the lexicon list are slightly more likely to be recorded as associates than words which appear later in the word list. In real life, this would be equivalent to RED (a high frequency word) being more likely to appear as an associate than PINK (a lower frequency word), and RED would thus be more likely to appear twice in a set of associations than PINK would. This seems like a plausible explanation for the increased hit rate in this model.

3.2: Small world models

So far, then, the data we have reported suggest that changing the way we model the underlying structure of our association network does not make a huge difference to the results returned by the simulator. The biggest difference occurs when we impose a developmental ordering constraint on the formation of associations, but even with this tight constraint, the data generated by the simulator does not change very much. The probability of a hit being registered increases slightly, but in other respects the simulations do not result in a radically different set of outcomes. Overall, the data reported in figures 1 to 5 are remarkably consistent.

However, a number of writers have recently suggested that random structures are not a good model for lexical networks, and that human lexicons may exhibit the properties of a "small world" (Watts and Strogatz 1998, Ferrer i Cancho and Solé 2001) . The main feature of small world networks is that most nodes in the network are connected to a small number of closely related nodes, and only a few connections go from one of these clusters to another cluster. An example of this type of structure is shown in Figure 6:

Figure 6: A small world lexicon.



In this illustration the words in the lexical network, represented by small squares, are organised into sixteen clusters, where each member of the cluster is linked immediately to several other members in the cluster. A small number of links join the clusters to each other, but these long-range links are few and appear to be less important than the links which operate within each cluster.

What effects do a structure of this sort impose on our simulated data? The answer to this question is not straightforward, as it is not immediately obvious what characteristics of small world lexicons we need to program into our simulations. As a first stab, however, we devised a model in which all the words in our lexicon are grouped into 20 clusters, each consisting of 50 words. Within these clusters, associations are formed at random. In addition to these clusters, we also built in an additional fifty long-range links which went from one cluster to another. In this way of modelling a small world lexicon, our lexicon looks something like table 4.

In this illustration, each word has four associates, with each of the four associates coming from a set of fifty words. All the links in the first set come from the first fifty words in the lexicon, while all the links in the second set are taken from the range 101 to 150, and all the links in the final set come from the range 951 to 1000. In addition, some words have an extra association, which links the cluster to another cluster.

The data shown in figure 7 comes from a set of simulations where the lexicon is structured

Table 4: a fragment of a small world lexicon.

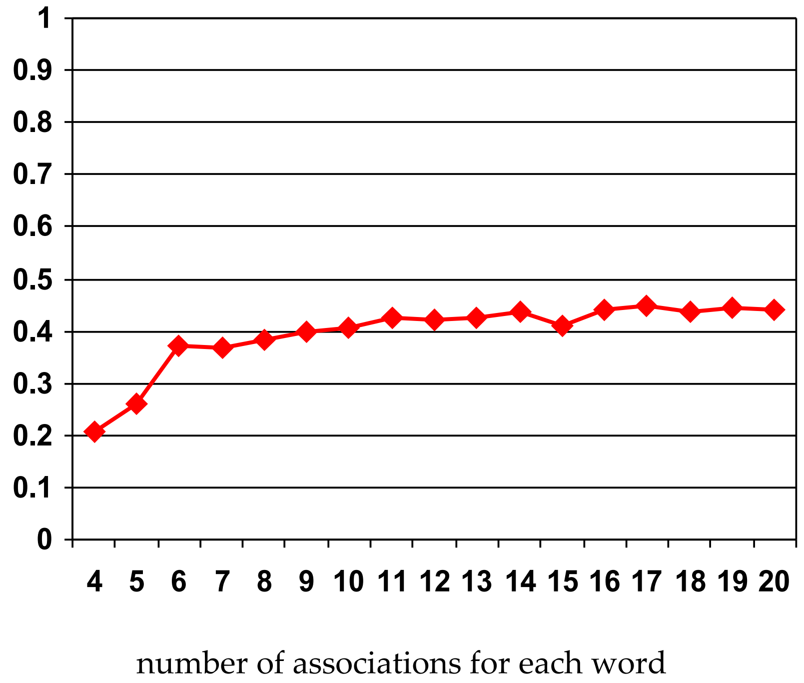
word 0001	0002	0012	0015	0020	
word 0002	0013	0003	0001	0015	
word 0003	0033	0010	0001	0009	
word 0004	0012	0031	0042	0014	
word 0005	0003	0028	0047	0020	0656
…					
word 0101	0115	0118	0103	0102	
word 0102	1122	0117	0124	0116	
word 0103	0133	0114	0145	0128	
word 0104	0141	0116	0138	0130	
word 0105	0105	0101	0104	0110	0235
…					
word 0996	0981	0985	0989	0991	
word 0997	0985	0996	0999	0984	
word 0998	0972	0983	0961	0974	
word 0999	0962	0974	0985	0990	0123
word 1000	0982	0993	0999	0962	

into 20 clusters of 50 words, the number of long-range links is set at 50, and the number of links allowed to each word varies from four to 20.

Surprisingly, this way of simulating a lexicon generates data which look very different from the data in figures 1 through 5. Although the probability of a hit rises slightly as the number of links per word grows, the rate of growth is painfully slow. It appears to reach an asymptote at around twenty links per word, when the probability of a hit is just over 40%.

On reflection, it is not difficult to figure out why these figures look so very different from our earlier simulations. In the small world simulation, the critical factors must be the size of the clusters, and the probability of a stimulus set containing two words from the same cluster. If the clusters are small, then the probability of getting two stimulus words from the same cluster is also small; on the other hand, if the cluster size is large, then the probability of getting two words in a stimulus set from the same cluster increases. At the same time, if the clusters are small, then the chances of two words from the same cluster sharing a common associate will increase, while if the clusters are very large, then the chances of a common associate for two words from the same cluster will decrease. This suggests that there may be a complex interplay between cluster size and number of associations per word in small world lexicons. The role of the long range associations is more difficult to predict, however and this suggests that it would be worthwhile to look in

Figure 7: p(hit) in a small world network
clusters=20, longlinks=50, shortlinks 4 to 20

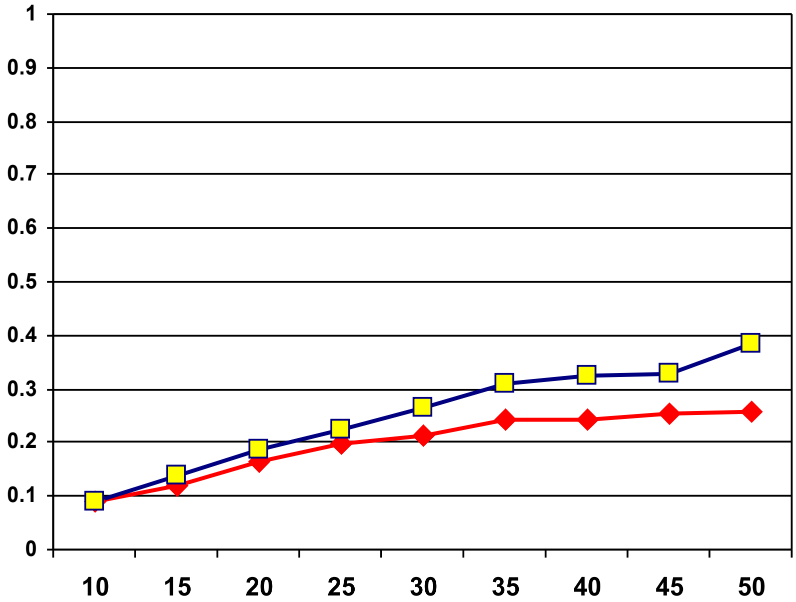


more detail at a range of different small world models, where cluster size and number of long range links are varied. A preliminary exploration of these issues is reported in Figures 8 , 9 and 10.

Figure 8 shows the probability of a hit being registered in a set of 5 randomly selected stimulus words from a small world lexicon where cluster size varies from 10 to 50 words, and the number of links per word is 5 or 8. In this illustration, the number of long range links is held constant at 50. Figure 8 suggests that cluster size has some impact on the likelihood of a hit being registered, as long as the clusters are relatively small. When the clusters become larger, the number of associations per word appears to emerge as the more important factor. Thus, for small cluster sizes, there is very little difference between a lexicon where each word has five or eight links, but for larger clusters, there does appear to be a difference which can be ascribed to the number of associates each word is allocated.

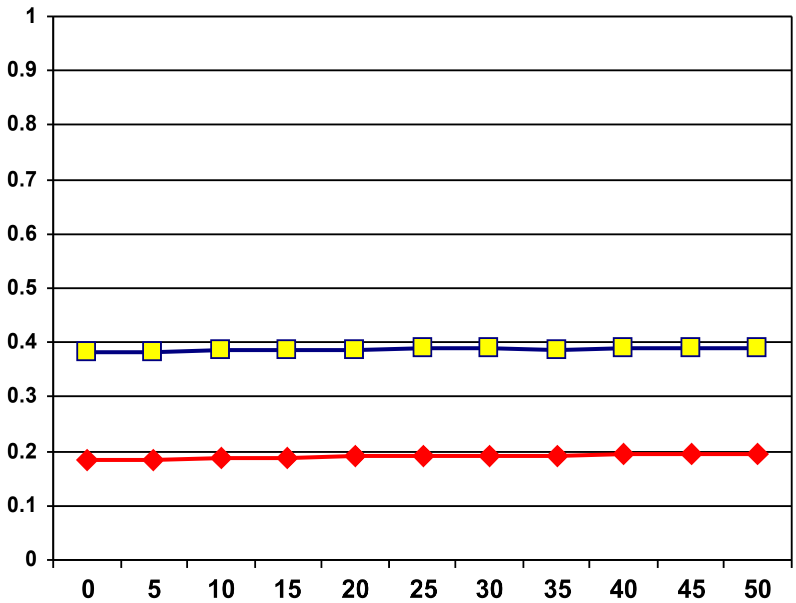
Figure 9 shows the effect of varying the number of long range links when cluster size and number of links per word are held constant. In this illustration, the number of links per word is held constant at eight, and data from two cluster sizes is reported, namely clusters of 20 or 50 words. Surprisingly, varying the number of long range links from 0 to 50 seems to make very little difference to the outcome of these simulations. Increasing the number of long range links over this range increases the probability of a hit being registered by only a tiny amount. Cluster size is a much more important factor, with larger clusters returning a higher probability of registering a hit.

Figure 8: small world networks
longlinks=50 shortlinks=5 or 8 cluster size = 10 to 50



cluster size

Figure 9: s**mall world networks**
shortlinks=8 longlinks=0 to 50 cluster size =20 or 50

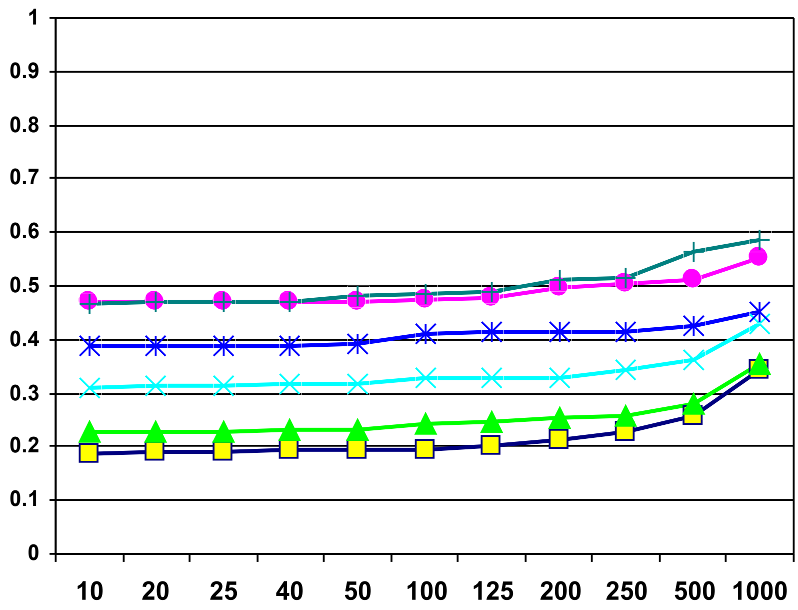


cluster size

Figure 10 shows a more detailed examination of the interaction between cluster size and the number of long range associations. In this figure, cluster size is allowed to vary from 10 to 125 words, while the number of long links is allowed to vary from 10 to 1000. In all cases, the number of association links allowed to each word is held constant at 8. The data suggests very clearly that long range links have only a miniscule effect on the probability of a hit being registered as long as the number of long range links remains small relative to the overall size of the lexicon.

Fi**gure 10: small world lexicons**

shortlinks=8 cluster size= 10 to 125 long links= 10 to 1,000

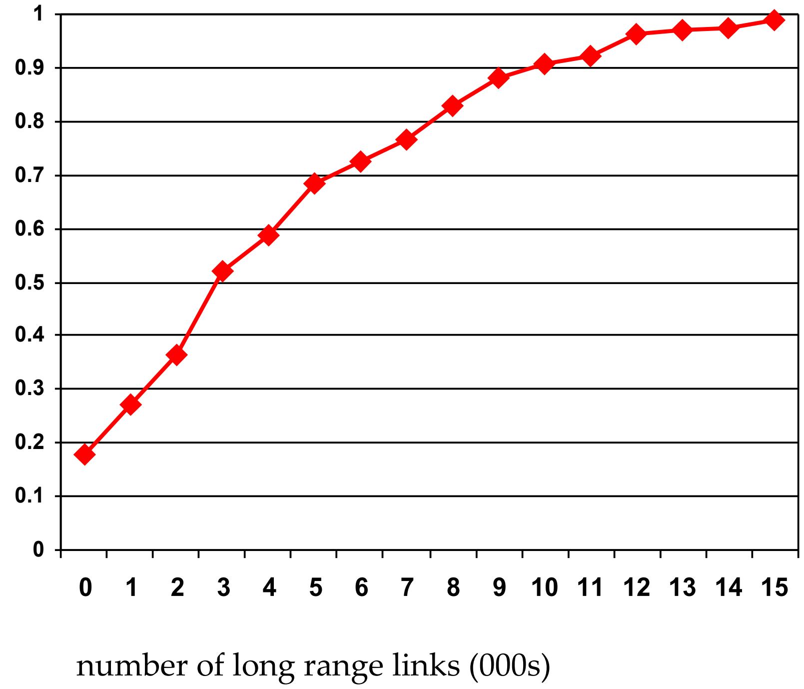


number of long range links

However there is a tantalising hint in the data shown in figure 10 that the probability of a hit being registered might increase if the number of long-range links is allowed to increase until these links form a significant proportion of the total number of links in the model lexicon. Figure 11 examines this possibility. This illustration shows data from a small world model in which we have twenty clusters of fifty words. Within each cluster, each word has five links to other words in the cluster. On top of this basic structure, I have varied the number of long range links from zero to 15,000. What Figure 11 shows is that the number of long range links is indeed the critical factor in determining the probability of a hit being registered., and the overall shape of the curve in figure 11 is again very close to the data reported in our earlier figures. Bearing in mind that the within-cluster associations in this model add another 5000 links to the total (each of the 1000 words has five within-cluster links), it probably makes sense to see the data in figure 11 as covering the range 5,000 to 20,000 links, and if we recalibrate the data in this way, we again have a data set which matches almost exactly the data reproduced in figure 2.

Figure 11: small world lexicons

shortlinks=5 cluster size=50 longlinks=0 to 15,000



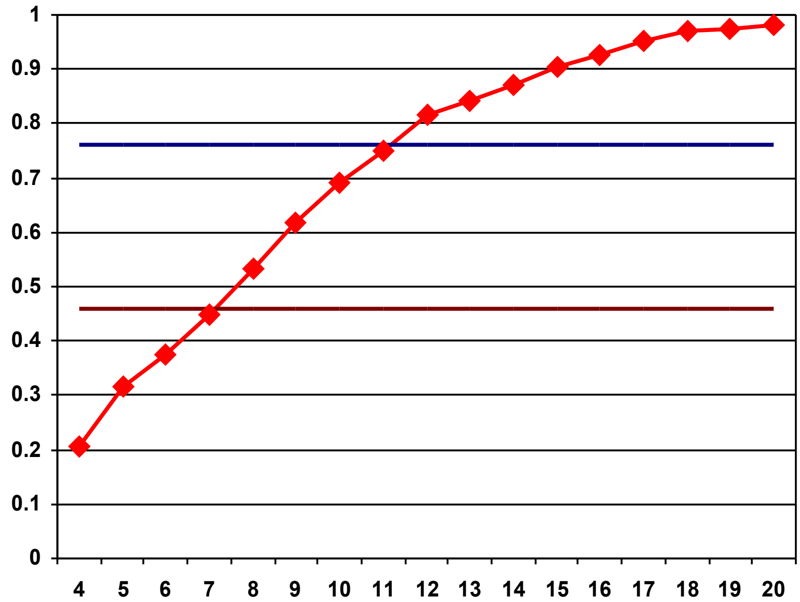
5: Discussion

With the data reported in figure 11, we have, it seems, pretty much returned to our starting point. We have examined the behaviour of a number of differently structured model lexicons, and we have discovered that the local structure of these models has a negligible effect on the probability of a pair of associated words being found in a random selection of five words. The only factor which emerges as important in these models is the overall number of associational links in the lexicon. This is a surprising finding, and it has a number of interesting implications.

Wilks, and Meara(2002) interpreted their original data as showing that words in their native speakers' lexicons had a greater number of connections than did words in their non-native speakers' lexicons. The differences were not great - native speakers were judged to have about eleven links per word, while non-native speakers were judged to have about seven. Meara (1996) and Meara and Wolter (2004) had suggested that a measure of this sort might have formed the basis of a measure of lexical organisation in an L2, and that this measure might be used to supplement the more commonly used measures of vocabulary depth. Unfortunately, the small size of this difference between L1 speakers and L2 speakers in Wilks, Meara and Wolter's (2005) study, and the difficulty they found in interpreting their data meaningfully left them very pessimistic about the possibility of developing a measure of this sort. However, if the local structure of their lexicons is not the critical factor which determines how speakers behave in our experimental task, then this pessimistic conclusion deserves to be re-visited.

Figure 12 shows the data first reported in Figure 2, with the addition of the real-life experimental data reported in Wilks, Meara and Wolter (2005). In this figure, the upper horizontal line shows the probability of a hit in the native speaker data, while the lower horizontal line indicates the probability of a hit in the learner data. WM&W interpreted these data in terms of the number of links per word, but in the light of the discussion in the previous section, it now seems obvious that we should reinterpret the data in terms of the overall number of associational links in the Ss' lexicons. Using this approach, WM&W's data suggests that L1 speakers have about 11,500 links, while the non-native speakers have around 7,500 links giving us a difference of about 4,000 links. This figure is much easier to interpret than the mean links per word figure we used in our earlier paper, and it is easy to see what the data might mean in real life. More importantly, the total links figure is very much easier to incorporate into a model of lexical growth - the process of adding a new link is straightforward and transparent in a way that our original concept of mean links per word was not.

Figure 12: Random Links Variable N and data from Wilks Meara and Wolter



number of long range links (000s)

This conclusion breathes new life into Meara's suggestion that it might be possible to construct a measure of overall lexical organisation which could be used to study changes in the way learners' lexicons change as their L2 proficiency improves over time, and we hope to be able to report progress in this area in future studies. What seems to be needed is a standardised instrument such as the five-word task described in Wilks, Meara and Wolter, and an agreed way of interpreting the results this instrument generates in terms of the overall number of connections the target lexicon contains. Neither of these requirements looks impossibly difficult to achieve.

However, the main point of this paper goes rather further than these practical suggestions. In a paper which was highly critical of some earlier simulation work that we had carried out, Laufer (2005) dismissed simulations as a "convenient escape from the real world". Although Laufer's highly critical approach to our work is an extreme position on this issue, she voiced what seems to be a widely held view among SLA researchers that simulations are simply not an appropriate way of researching the processes of acquiring a second language. We have always argued that this view is short-sighted. We believe that simulations can throw valuable light on the way we interpret the data generated in experiments with real subjects, and that simulations can help us ask better research questions and help us design better research instruments to answer them. This paper has been a good example of this type of interaction between simulations and "real world" research. What we have done in these simulations is to take a commonly used metaphor about the way lexicons are structured, and explore how far we can go with it using a simple data collection instrument, the five-word task. It turns out that the metaphor does not work quite as we might expect. The metaphor leads us to expect that local organisation is the most important feature of a network, but working with the metaphor in detail has forced us to reach a different conclusion: overall structure seems to be more important than local structure - at least as far as the five-word task is concerned. Significantly, this overall structure can be conveniently summarised by a single parameter - the total number of links in the network - and for practical purposes, it seems as though we might be able to ignore other factors that looked as though they might be important, but turn out not to be. Put simply, the simulations suggest that our initial approach to the question of lexical organisation in L2 speakers may have been unnecessarily complex.

Additionally, the simulations reported here provide us with some valuable feedback about the way our experimental task works. The simulations suggest that the five-word task should work well over a wide range of proficiency levels - only when the number of links reaches very high levels do simulations of the five-word task fail to show an increase in the number of hits registered. This level seems to be well above what we find even with native speaker subjects, so the lack of sensitivity at this level is not likely to be a serious problem. The simulations also seem to indicate that the five-word task might be capable of registering relatively small amounts of growth in lexical structure, particularly at low levels of L2 proficiency. The data suggest that a 50 item test should be sensitive enough to register an increase of 500 associational links in a small lexicon, and a 100 item test should be considerably more sensitive to small changes in the number of links in the target vocabulary. This level of sensitivity is probably good enough to register changes in a lexicon over relatively short periods of time, such as the ones typically used in classroom research. This is an important consideration, since some other widely used measures do not seem to be sensitive in this way (Meara 2005).

6: Conclusion

To summarise, the data reported here is a good example of the way simulations interact both with theory and with practical data collection. Far from being "a convenient escape from the real world", simulations offer a way of thinking about the data collected in real experiments, and suggest ways of improving the way we collect this data in the first place. Work of this sort inevitably introduces some simplifications, but to be frank, most research does this too. The difference is that in simulation work the simplifications are explicit and overt rather than hidden and covert. In good simulation research, we can explore the implications of making these simplifications in a way which is just not possible for logistic reasons when we work with real subjects in experimental settings.

I hope that readers of this paper will share my view that the approach I have used here is both illuminating and exciting, and that the ideas I have explored here will perhaps make some critical researchers think again about practical applications of simulations in SLA research.

7: Bibliography

Aitchison, J. 1987
Words in the Mind. Oxford: Basil Blackwell.
Bogaards, P. 1994.
Le vocabulaire dans l'apprentissage des langues étrangères. Paris: Didier.
Ferrer i Cancho, R and RV Solé. 2001.
The small world of human language. Proceeding of the Royal Society B, 268, 2261.
Gougenheim, G, R Michéa, P Rivenc and A Sauvageot. 1956.
L'élaboration du français élémentaire. Paris: Didier.
Laufer, B. 2006.
Lexical frequency profiles: from Monte Carlo to the Real World. A response to Meara. *Applied Linguistics* 26, 581-587.
Meara, PM. 1996.
The dimensions of lexical competence. In: G Brown, K Malmkjaer and J Wiliams (eds.) *Performance and Competence in Second Language Acquisition.* Cambridge: Cambridge University Press.
Meara, PM. 2005.
Lexical Frequency Profiles: a Monte Carlo Analysis. *Applied Linguistics* 26,1, 32-47.
MonteCarlo
Meara, PM and B Wolter. 2004.
V_Links: beyond vocabulary depth. *Angles on the English Speaking World*, 4, 85-96.
Watts, DJ. 2003.
Small worlds: the dynamics of networks between order and randomness. Princeton, N.J.: Princeton University Press.
Watts, DJ and SH Strogatz. 1998
Collective dynamics of small world networks. *Nature,* June 4; 393(6604) 409-10.
Wilks, C and PM Meara. 2002.
Untangling word webs: graph theory and the notion of density in second language word association networks. *Second Language Research* 18,4, 303-324.
Wilks, C, PM Meara and B Wolter. 2005.
A further note on simulating word association behaviour in an L2. *Second Language Research* 21,4, 359-372.