Graph Theoretic Features of the Adult Mental Lexicon Predict Language Production in Mandarin: Clustering Coefficient

Karl David Neergaard
The Hong Kong Polytechnic University
136 Shanghai St. 7/F
Hong Kong
karl.neergaard@connect.polyu.hk

Chu-Ren Huang
The Hong Kong Polytechnic University
11 Yuk Choi Rd.
Hong Kong
churen.huang@polyu.edu.hk

Abstract

Graph theory has recently been used to explore the mathematical structure of the mental lexicon. In this study we tested the influence of graph measures on Mandarin speech production. Thirty-six native Mandarin-speaking adults took part in a shadowing task containing 194 monosyllabic words, 94 of which consisted of 3 phonemes and were the items under analysis. Linear mixed effect modeling revealed that clustering coefficient (C) predicted spoken production of Mandarin monosyllabic words, while network degree, in this case its phonological neighborhood density (PND) failed to account for lexical processing. High C resulted in shorter reaction times, contrary to evidence in English. While these findings suggest that lexical processing is affected by the network structure of the mental lexicon, they also suggest that language specific traits lead to differing behavioral outcomes. While PND can be understood as the underlying lattice for which a similarity network is created, lexical selection is not affected by only a target word's neighbors but instead the level of interconnectivity of words (C) within the network.

1 Introduction

Graph theory is currently an active tool within the language sciences. Networks constructed from the semantic knowledge of children have shown typical versus disordered development (Beckage et al., 2011) and helped to explain the growth of vocabulary (Hills et al., 2009). The network structure of phonological networks has been found to influence children's productive vocabulary development and failed lexical retrieval in adults (Vitevitch et al., 2014). The new methodology coming to form involves the combination of graph theoretic models and psycholinguistic tasks, allowing for a view into the lexicon to examine language processing according to structural relations.

The manner in which a phonological network is constructed is through what is known as phonological neighborhood density (PND), which is a similarity metric that involves the addition, deletion or substitution of a single phoneme (Vitevitch, 2008). Thus, in the network, words (nodes) are connected (edges) to one another based on their sound similarity. Words that are connected via this similarity are known as neighbors and give us the network feature known as degree (*k*). In the psycholinguistic literature PND has been extensively investigated. It has been shown to influence word recognition (Luce and Pisoni, 1998), production (Sadat et al., 2014), and word learning (Storkel et al., 2006) to just name a few.

Once the network is built, other measures are then available, such as each node's clustering coef-

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ficient (C). C is the number of triangles made in relation to a given node. In terms of the mental lexicon, this presents us with a measure of how interconnected a word's neighbors are with each other. It has been illustrated with an English lexicon that PND and C are not equivalent measures in that they do not correlate with each other (Chan and Vitevitch, 2009). The role of C has been examined in word recognition (Chan and Vitevitch, 2009; Yates, 2013), and picture naming (Chan and Vitevitch, 2010), allowing for the tentative statement that, at least for English speakers, low C words are produced faster and more accurately than high C words.

While research into the network features of the mental lexicon has advanced rapidly, there has been an inordinate stress upon European languages, specifically English. Mandarin, to date has no evidence of either a PND or C effect on language processing, despite several attempts (Myers and Tsay, 2005; Tsai, 2007). One reason for such a disparaging lack might lie in the complexity of the Mandarin mental lexicon, specifically the role that tone plays. Indeed, Vitevitch and Stamer (2006) propose that differences in processing found between languages are likely to be found due to the linguistic differences exhibited by many languages.

In comparison to English, Mandarin has a small syllable inventory (~400 without tone). This language specific feature might suggest a lexicon that would be more dense, leading to increased competition between neighbors. Tone however creates distance between what would be otherwise similar sounding words. Tone, in fact has been shown to be the initial guiding point for phonological manipulation (Neergaard & Huang, 2016; Weiner & Turnball, 2015).

The purpose of the current study is to investigate the role of network characteristics in a tonal language through the implementation of an auditory shadowing task.

2 Methods

2.1 Participants

The current results come from the spoken production of Thirty-six native Mandarin speakers (Female: 20). One participant was excluded from the analysis due to misunderstanding the task instructions. None of the participants reported speech, hearing, or visual disorders.

2.2 Stimuli

The stimuli, recorded by a female native Mandarin speaker from the Beijing area, consisted of 193 Mandarin monosyllabic words. All stimuli were 415ms in duration. Target stimuli, which can be seen in Appendix A, consisted of 94 words that were 3 phonemes in length. Filler words consisted of 99 monosyllabic words that contained 1, 2 and 4 phonemes. Filler words were used in the task so as to preclude the participants' ability to predict the structure of upcoming words. Presentation order

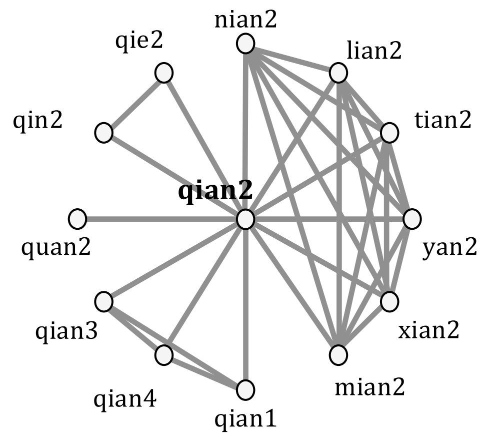

Figure 1. The word level network for qian2 /tɕʻiɛn2/ 前 (PND: 12; C: .83)

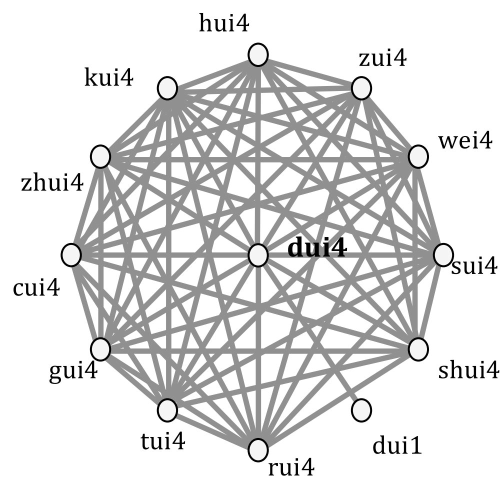

Figure 2. The word level network for dui4/ tueɪ4/对, (PND: 12; C: .29)

was pseudo-randomized so as not to allow for the serial presentation of words that began with the same onset or that had the same tone.

The stimulus words were selected from a database of movie subtitles (Subtlex-CH: Cai and Brysbaert, 2010). As is common amongst databases that provide calculations of PND and other lexical information (See Marian et al., 2012 for an in-depth discussion), a representative sample of orthographic words is chosen from either a dictionary or subtitle movie corpora. The current study calculated PND and four of the following word characteristics from the top 17 thousand entries of phonological words. The pinyin transcriptions of the Subltex-CH database were made using the Lingua Sinica corpus (Chen et al., 1996). Phonological representations of spoken Mandarin were then taken from Neergaard and Huang (2016) according to the maximal syllable structure: CVVX plus tone.

The frequencies of homophonous words were summed together such that spoken word frequency (SWF) (M: 0.0271 per-million; SD: 0.0556 per-million), and homophone density (HD) could be calculated. HD (M: 5; SD: 4) was calculated based on the number of orthographic words that were used in the corpus per each phonological word. Neighborhood frequency (NF) (M: 18,1950; SD: 20,2318) was calculated from the combined frequency of a word's neighbors. C (M: 0.4065; SD: 0.1623) was calculated through the use of the network analysis tool, Gephi (Bastian et al., 2009). It should be noted that the correlation between PND (M: 14; SD: 5) and C within our stimuli set was low: 0.3. For an illustration of the difference between PND and C see Figures 1 and 2. Note that both represent words with equivalent densities.

2.3 Procedure

Participants were seated in a quiet room in front of a computer running experimental software, E-Prime 2.0 (Psychology Software Tools, 2012). They were instructed to repeat experimenter-provided auditory stimuli into a headset as quickly as possible. The onset of each trial was activated when a participant spoke via a PST Serial Response Box. They were given a practice set of 10 words.

Each trial consisted of the same sequence: "下个词" (next word) was presented at the center of the screen for 1000ms, followed by a blank screen and the onset of the target audio which changed either upon the onset of a participant's spoken response or a maximum of 3000ms, then finally a pause of 3000ms. The entire experiment took less than 15 minutes and was recorded on a second computer using Audacity 2.0.6.

Reaction times were measured offline using SayWhen (Jansen and Watter, 2008). The audio recordings were also used to transcribe the participants' spoken production by two native-Mandarin speaking volunteers. Incorrect responses were removed from the analysis, accounting for less than 6% of the data.

3 Results

Statistical analyses were done using linear mixed effect modeling (lmerTest in R). The first constructed model revealed that SWF (t = -2.462; p = 0.014) and C (t = -2.771; p = 0.0056) were predictors in the production of Mandarin monosyllabic words, while PND, NF, and HD were non-significant. In order to eliminate the effect of SWF on the other predictors, 96 trials, identified as outliers, were removed from the total of 3,177 trials. The removal of the outliers, which accounted for 3% of the total, limited the responses' reaction time to within 450 and 1000ms.

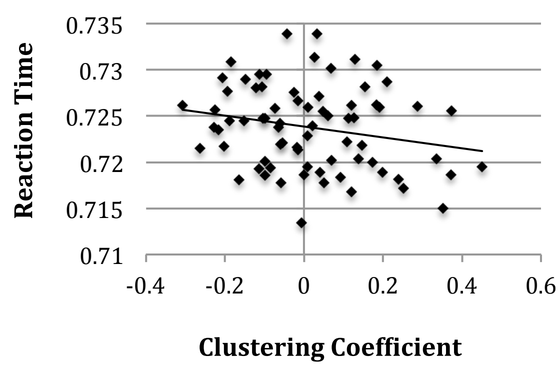

Figure 3. The effect of Mandarin clustering coefficient on reaction time

A second model was then created according to stepwise backwards model comparison. While the SWF effect disappeared, and none of the other predictors changed status, the effect of C remained through each successive model iteration (Std. Error: 0.00820; df: 3037; t = -3.27; p = 0.001). Unique to this study, high C values resulted in shorter reaction times as can be seen in Figure 3.

4 Conclusion

The present study is the first to find an influence of network measures on language production in a tonal language. Of particular note is the fact that the direction of the C effect is contrary to that of the English findings (Chan and Vitevitch, 2009, 2010). While the two prior studies implemented different tasks to what is currently featured, the direction was the same for English speakers: words with low C were produced faster and more accurately than words with high C. The present results, in contrast, suggest that the greater the interconnectivity of phonological words the less the competition for lexical selection.

One direction for further investigation is the role that network density plays across the Mandarin lexicon, specifically during development. If, like the present findings suggest, greater connectivity speeds processing, then this would imply the emergence of an adaptive trait learned through the acquisition of highly similar words. Such a language specific adaptation would have implications for vocabulary acquisition and possibly be of note for children with phonological delay (Gierut et al., 1999).

An alternative hypothesis is that a significant C effect concurrent with a null PND effect points to an error in the model's construction. There have been multiple proposals as to the segmentation of the Mandarin syllable (Duanmu, 2009). In the current study we examined a segmental approach with phonological tone. Future experimental designs would benefit from contrasting stimuli that have been calculated according to multiple segmentation schemas.

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Appendix A. Experimental Stimuli

Stimulus	Tone	SWF	HD	PND	NF	C
ban1	1	0.0077	8	20	83792	0.3895
bei3	3	0.0010	1	9	325390	0.4444
bing1	1	0.0025	2	14	165280	0.2857
bo1	1	0.0027	7	13	241279	0.6154
cai2	2	0.0370	4	15	214339	0.4000
cong2	2	0.0473	3	9	24192	0.4444
cuo4	4	0.0363	4	18	431772	0.6928
dai4	4	0.0385	10	21	896543	0.5333
die1	1	0.0003	1	13	46232	0.4744
fei2	2	0.0011	2	9	279495	0.5000
fen4	4	0.0159	6	15	39299	0.4571
feng1	1	0.0115	9	17	35947	0.5809
gai1	1	0.0342	1	19	108154	0.4327
gang1	1	0.0115	7	23	133498	0.3913
gao3	3	0.0185	3	21	151546	0.5190
gua4	4	0.0035	2	11	167761	0.2000

gun3	3	0.0040	2	12	33905	0.3030
hei1	1	0.0457	3	6	43405	0.4667
hen3	3	0.2011	3	11	24792	0.5273
hong2	2	0.0031	8	11	64484	0.3091
hou4	4	0.0226	4	16	450310	0.6583
hua2	2	0.0026	5	9	199436	0.2222
hun4	4	0.0035	2	16	227090	0.2917
huo2	2	0.0115	1	14	334170	0.4396
jia1	1	0.0332	13	12	106018	0.2121
jie1	1	0.0148	8	18	125483	0.3007
jin4	4	0.0247	10	11	104577	0.2000
jing3	3	0.0054	9	16	126033	0.3083
jue2	2	0.0026	13	5	16343	0.1000
jun1	1	0.0016	5	7	9095	0.1429
kua3	3	0.0004	1	9	8227	0.2222
kun4	4	0.0015	1	14	117829	0.3516
lao3	3	0.0177	4	22	1062897	0.4762
lie4	4	0.0016	8	12	112347	0.3333
lun2	2	0.0032	4	9	12206	0.2222
mai3	3	0.0158	1	15	48933	0.4476
mao1	1	0.0035	1	19	350311	0.5439
mei2	2	0.1617	13	9	129539	0.4444
men2	2	0.0089	2	12	248251	0.3485
min2	2	0.0005	4	11	45135	0.2182
ming2	2	0.0115	7	13	75796	0.3077
mo2	2	0.0035	8	12	176888	0.5909
nan2	2	0.0171	5	15	98327	0.5524
nong4	4	0.0136	1	9	83669	0.7778
pao4	4	0.0014	3	23	798622	0.4545
pei2	2	0.0035	5	9	274588	0.4444
pin1	1	0.0012	1	13	42567	0.2051
qia1	1	0.0004	1	9	60204	0.2222
qin2	2	0.0007	8	11	135499	0.2545
qing3	3	0.0306	2	14	56346	0.3516
que1	1	0.0007	2	7	22955	0.1905
qun2	2	0.0032	2	5	13142	0.2000
ran2	2	0.0007	3	14	260802	0.6044
rang4	4	0.1238	2	16	180346	0.7583
ren2	2	0.1950	5	11	24812	0.4000
reng1	1	0.0041	1	14	41806	0.8571
rou4	4	0.0025	1	15	123569	0.7429
ruo4	4	0.0022	5	17	467943	0.7794
san3	3	0.0002	2	22	58109	0.5974
sang1	1	0.0004	2	20	113667	0.5158
shan1	1	0.0034	12	19	81325	0.4152
shang4	4	0.1147	4	21	204382	0.4667

sheng3	3	0.0014	1	13	58529	0.3205
shua1	1	0.0006	2	12	299841	0.2424
shuo1	1	0.2270	1	13	25019	0.5897
song4	4	0.0133	5	10	84434	0.6444
tang3	3	0.0023	4	19	57176	0.3626
ting1	1	0.0555	3	13	76196	0.3077
wai4	4	0.0041	1	26	773415	0.3908
wan2	2	0.0244	6	20	201339	0.3421
wang4	4	0.0077	4	23	319519	0.4150
wei2	2	0.0493	13	13	289022	0.3077
wen4	4	0.0205	3	14	40995	0.5275
xia4	4	0.0557	4	11	115839	0.2182
xie2	2	0.0028	12	12	92857	0.1818
xin1	1	0.0265	9	12	69575	0.2576
xue2	2	0.0062	1	8	8282	0.1786
xun1	1	0.0004	5	7	34976	0.1429
yan3	3	0.0064	5	15	236670	0.3810
yang3	3	0.0036	4	22	317363	0.2944
yao4	4	0.2435	4	30	696392	0.3471
yong3	3	0.0010	12	14	381844	0.4066
you3	3	0.2896	6	22	175262	0.3463
yuan2	2	0.0121	15	7	24682	0.1905
zai3	3	0.0007	2	15	527024	0.4667
zao3	3	0.0129	5	21	193120	0.5190
zeng4	4	0.0001	3	13	42450	0.5897
zhan4	4	0.0132	9	22	245617	0.4286
zhen4	4	0.0024	7	15	469888	0.4476
zheng4	4	0.0207	5	16	315381	0.4000
zhong1	1	0.0382	6	14	56887	0.4176
zhua1	1	0.0084	1	10	34372	0.3111
zong3	3	0.0099	1	12	92516	0.5606
zun1	1	0.0004	5	8	6180	0.5357

Note: Stimulus words are presented in pinyin; SWF is spoken word frequency; HD is homophone density; PND is phonological neighborhood density; NF is neighborhood frequency; C is clustering coefficient