Phonological Neighborhood Density Modulates Errors In Spoken Word Recognition

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Abstract

The present study examined how differences in onset (cohort) and offset (rhyme) neighborhood density influence the types of spoken word recognition errors made by listeners. Simulations of the TRACE model were used to derive preliminary predictions. Younger (N=15) and older (N=15) adults identified spoken words presented in moderate noise. Participants exhibited the standard inhibitory effect of phonological neighborhood density: slower recognition of spoken words from denser neighborhoods, with a larger effect for older adults. Most errors were phonological neighbors with few unrelated errors. However, the manipulation of cohort and rhyme density produced an unexpected reversal: the relative proportion of cohort vs. rhyme errors was biased toward cohorts when cohort density was low or when rhyme density was high, and toward rhymes when cohort density was high or rhyme density was low. These results are not consistent with the TRACE simulations and suggest a more complex pattern of lexical competition.

Keywords: neighborhood density; spoken word recognition; lexical selection; error type.

Introduction

Spoken word recognition requires listeners to map sequential phonological input onto stored lexical candidates. It is widely agreed that this mapping occurs incrementally, sequentially, and interactively: starting with the onset of speech input, proceeding along with the sequential speech input, and involving both bottom-up and top-down information flow (for a review see, e.g., Magnuson, Mirman, & Myers, 2013). One consequence of the incremental nature of spoken word recognition is the parallel activation of multiple lexical candidates based on partial match to the unfolding speech input and competition between those candidates. This competition can be easily demonstrated by phonological neighborhood density effects: words with many phonological neighbors are recognized more slowly and less accurately than words with fewer phonological neighbors (e.g., Luce & Large 2001; Luce & Pisoni 1998; Luce, Pisoni & Goldinger, 1990; Magnuson, Dixon, Tanenhaus & Aslin, 2007; Sommers, 1996).

The most common definition of phonological neighbors is known as the "one phoneme rule": a neighbor differs from the target word by no more than one phoneme through deletion, addition, or substitution (also called the DAS rule). Due to the sequential nature of speech input, the location of overlap also influences competition. For example, *cohort* competitors share the onset of the spoken word (i.e., first two phonemes), so they are activated early in processing and are associated with a larger competition effect relative to rhyme competitors, which share the offset of the spoken word (i.e., vowel and coda), and consequently become active later, when the target word (along with its cohort competitors) is already highly activated and therefore more strongly suppressing any new competitors (e.g., Allopenna, Magnuson & Tanenhaus, 1998; Magnuson et al., 2007).

The addition of noise tends to increase competition from offset neighbors more than onset neighbors, regardless of its source (broadband noise: Brouwer & Bradlow, 2011; rhyme neighbors spoken in the background: Brouwer & Bradlow, in press) and locus of occurrence (concurrently with the target: Brouwer & Bradlow, 2011; somewhere in the sentential context: McQueen & Huetting, 2012). Moreover, older adults experience more competition from rhymes in noisy backgrounds than younger adults do (Ben-David et al., 2011), suggesting that age-related declines in hearing acuity may have a similar "noise" effect (Lash, Rogers, Zoller & Wingfield, 2013).

Analyses of error types have provided unique insights into the cognitive and neural architecture of spoken word production (e.g., Dell, Schwartz, Martin, Saffran & Gagnon, 1997; Schwartz, Dell, Martin, Gahl & Sobel, 2006; see Schwartz, 2014 for a review). To our knowledge, a similar analysis of overt error types in spoken word recognition has not been attempted. In the current study, we examined the relative proportion of cohort and rhyme errors during spoken word recognition as a function of cohort and rhyme neighborhood density.

Phonological neighbors have been generally found to exert an inhibitory effect on recognition of a spoken target word. However, they should also exert a facilitative effect through excitatory feedback connections that support the shared phonological units such as phonemes. For example, "beet" competes with "heat", but also sends feedback excitation to /i/ and /t/ phonemes, which send feedforward excitation to "heat", thus producing an indirect facilitative effect. In spoken word recognition this facilitative effect is generally weaker than the direct inhibitory effect, though this is different in other tasks (e.g., visual word recognition) and can be modulated by preview of response options (see Chen & Mirman, 2012; 2015). Recurrent facilitation may increase cohort errors for targets from dense cohort neighborhoods and increase rhyme errors for targets from dense rhyme neighborhoods. Bormann, Kulke, Wallesch and Blanken (2008) report an analogous error pattern in individuals with aphasia, who produced semantic errors more frequently for targets with many semantic neighbors, while omissions were more frequent for targets with few semantic neighbors. On the other hand, a dense cohort neighborhood may increase cohort ambiguity, possibly making rhyme errors more likely (and vice versa for rhyme neighborhoods). Further, since older adults exhibit increased rhyme competition relative to younger adults, younger adults may experience more competition from onsets, therefore producing more onset errors than older adults do.

As the above demonstrates, it is difficult to intuit the net effect of the combination of direct inhibition and recurrent facilitation on error types. Therefore, we conducted preliminary simulations of the TRACE model (McClelland & Elman, 1986) in order to empirically determine an initial set of predictions from a widely-accepted interactive activation and competition model of spoken word recognition.

Simulations

The simulations were conducted using the jTRACE implementation (Strauss, Harris & Magnuson, 2007) of the TRACE model of speech perception and spoken word recognition (McClelland & Elman, 1986). For each simulation, a target word was presented and response probabilities were computed using the R. D. Luce (1959) choice rule for four response options: the target word, a cohort competitor, a rhyme competitor, and a phonologically unrelated word. Minimal artificial lexicons were constructed to provide a simple context for testing effects of cohort and rhyme density. Each lexicon contained the same three critical quartets of words (target, cohort, rhyme, and unrelated). The base lexicon consisted of only those 12 words. Two additional lexicons were created by adding either four cohort or four rhyme competitors (to bring the total to 5 cohort or 5 rhyme competitors), and another two lexicons had an additional 5 cohort or 5 rhyme competitors (for a total of 10 cohort or 10 rhyme competitors). When the number of one kind of competitor was increased, the other competitor type was held constant (i.e., the lexicons with 1, 5, and 10 cohort neighbors contained only 1 rhyme neighbor; the lexicons with 1, 5, and 10 rhyme neighbors contained only one cohort neighbor). That is, we tested the same three sets of critical items at separately increasing numbers of cohort or rhyme competitors. Simulations were conducted using the default TRACE parameter set and with the addition of Gaussian noise (SD=0.5). The with-noise simulations were repeated 10 times to average over idiosyncratic noise samples.

Because participants in the behavioral experiment would be making forced-choice decisions between the target and specific cohort, rhyme, and unrelated distractors, for the simulations, lexical unit activation was converted into response probabilities among the defined set of four alternatives using the Luce choice rule. The Luce choice rule quantifies the activation of each response option relative to all other options and thereby provides one simple link between TRACE lexical unit activations and word recognition errors. The preliminary predictions were based on averages over cycles 5 to 40 because response probabilities were at baseline before cycle 5 and competition was essentially eliminated after cycle 40.

Figure 1 shows the TRACE-predicted patterns of cohort errors (top panel), rhyme errors (middle panel), and unrelated errors (bottom panel) as a function of increasing rhyme density (red lines) or cohort density (blue lines), for both no-noise (solid lines) and with-noise (dotted lines) simulations. Because the goal of these simulations was to derive preliminary predictions using highly simplified lexicons, the specific predicted values are not as important as the qualitative pattern of error types.

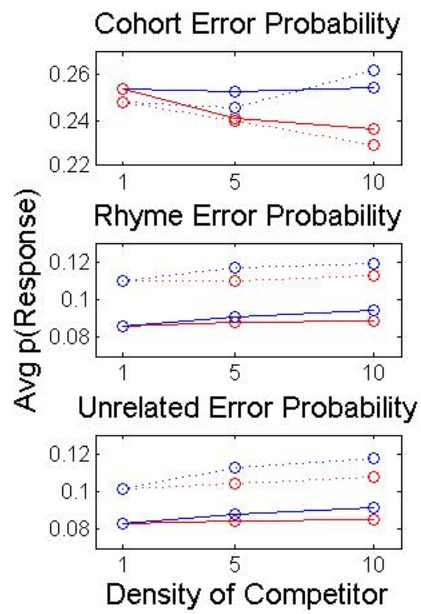

Figure 1: TRACE model predictions for effect of increasing rhyme density (red lines) or cohort density (blue lines) on probability of cohort errors (top panel), rhyme errors (middle panel), and unrelated errors (bottom panel). Solid lines show results of no-noise simulations, dotted lines show with-noise simulations. Note that the vertical axis scale differs in the top panel because cohort activations are substantially higher than rhyme and unrelated activations.

The simulation results predict that increasing cohort density (blue lines) should have a minimal (possibly increasing) effect on cohort errors (top panel) while producing more rhyme and unrelated errors (middle and bottom panels). Increasing rhyme density (red lines) should substantially decrease cohort errors while moderately increasing rhyme and unrelated errors.

The experiment was designed to provide new insights into the dynamics of lexical competition by considering error types in the context of these predictions.

Experiment

Method

Participants Two groups of participants with no history of neurological, language, or reading disorders completed the study: (1) 15 young adults (6 male, mean age = 21.5, age range = 18-38) recruited from Drexel University and (2) 15 older adults (8 male; mean age = 67.9, age range = 61-79 years) recruited from the MRRI Cognitive Rehabilitation Research Registry (Schwartz, Brecher, White & Klein, 2005), who showed no signs of cognitive impairment based on the Mini Mental State Examination (Folstein, Folstein & McHugh, 1975; mean score = 28.1).

Materials Stimuli were 600 monosyllabic English open class words (nouns and verbs), which were divided into 120 targets and 480 distractors. The phonological neighborhood of target words was separately manipulated at word onset (first two phonemes, i.e., cohort) and word offset (vowel and coda, i.e., rhyme). Cohort density (high vs. low) was operationalized as the number, $t(58) = 4.4$, $p < 0.0001$, and summed frequency, $t(58) = 4.23$, $p < 0.0001$, of onset neighbors, while the number and summed frequency of offset neighbors was held constant (all $p > 0.05$). Rhyme density was operationalized as the number, $t(58) = 10.47$, $p < 0.0001$, and summed frequency, $t(58) = 6.86$, $p < 0.0001$, of offset neighbors, while the number and summed frequency of onset neighbors was held constant (all $p > 0.05$). The manipulations of phonological neighborhood type and density resulted in four conditions of interest with 30 trials each: high-density cohorts, low-density cohorts, high-density rhymes and low-density rhymes (see Table 1). The conditions were matched on number of phonemes and lexical frequency using the American National Corpus (Ide & Suderman, 2004), as well as on the length of the auditory file (all $p > 0.05$). Distractors were of four types: cohort neighbors, rhyme neighbors, cohort neighbors of rhyme distractors and rhyme neighbors of cohort distractors, and did not differ in number of phonemes, frequency, phonological neighborhood density and cohort density from targets (all $p > 0.05$). All auditory targets were recorded by a female native English speaker in a quiet room and normalized at 60 dB prior to adding 62 dB of white noise to make word recognition more difficult.

Procedure Participants were seated at a comfortable distance (about 15 inches) from a computer monitor and asked to perform a spoken-to-written word matching task, consisting of 120 trials with a mid-way break. The task was modeled on identification of words in noise (e.g., Luce & Pisoni, 1998). Each trial began with a trial preparation screen presented for 2000 ms with a red circle in the center that decreased in size until it disappeared, at which point the auditory stimulus was presented over headphones. This was followed by a 1000 ms blank screen to allow auditory word recognition without bias from visually-presented response options. Finally, a 2 x 3 array of six response options was presented and remained on the screen until a response was made.

Table 1: Mean (SD) target word characteristics.

Measure	Cohort Density		Rhyme Density	
	High	Low	High	Low
Auditory file length (ms)	626.3 (95.19)	622.8 (90.7)	613.5 (98.66)	600.4 (102.85)
Number of phonemes	3.40 (0.5)	3.43 (0.5)	3.40 (0.62)	3.43 (0.68)
Log frequency	1.24 (0.68)	1.29 (0.54)	1.06 (0.33)	1.02 (0.28)
Number of neighbors	19.03 (9.69)	14.97 (8.34)	20.33 (8.99)	10.80 (5.33)
Summed freq. neighbors	23.24 (14.02)	18.04 (11.61)	22.91 (11.59)	11.04 (6.19)
Number cohort neighbors	96.37 (73.49)	35.27 (19.8)	48.63 (32.6)	57.60 (41.21)
Summed freq. cohort neigh	64.83 (48.8)	25.75 (13.48)	34.27 (22.75)	39.58 (27.34)
Number rhyme neighbors	18.97 (11.90)	14.60 (8.62)	24.47 (10.16)	4.70 (1.95)
Summed freq. rhyme neigh	24.71 (23.44)	17.88 (12.41)	31.04 (21.19)	4.35 (2.30)

The response array contained the target (e.g., CAP), a cohort distractor (e.g., CAT), a rhyme distractor (e.g., LAP), a cohort neighbor of the rhyme distractor (e.g., LAG), a rhyme neighbor of the cohort distractor (e.g., MAT), and an undecided response option (i.e., ?) to reduce guessing. See Table 2 for examples. This made it difficult to guess the target simply from the structure of the response array (i.e., the target was not the only option with phonologically related distractors; there were two other response options that also had cohort-related and rhyme-related distractors). The response options were presented in black capital letters against a white background and their locations were randomized on each trial.

Participants were instructed to select the cell containing the word they heard either using a mouse (younger adults) or using their hand on a touch-sensitive monitor (older adults). They were also encouraged to select the "?" response option whenever they were unable to recognize the target. Both speed and accuracy were stressed. A set of 20 practice trials preceded the experimental set.

Table 2: Stimulus examples.

Response	High Density	Low Density
Target	CAP	FOX
Cohort Distractor (CD)	CAT	FOG
Rhyme Distractor (RD)	LAP	BOX
Cohort Neighbor of RD	LAG	BOSS
Rhyme Neighbor of CD	MAT	JOG

Results

Reaction Times Correct-response latencies were analyzed using linear mixed-effects models with crossed random effects of subjects and items (Baayen, Davidson & Bates, 2008; Barr, Levy, Scheepers & Tily, 2013) implemented in R version 3.0.2 (R Core Team, 2013) using the lme4 package version 1.0-5 (Bates, Maechler, Bolker & Walker, 2013). The models included fixed effects of Density Level (High vs. Low), Density Type (Cohort vs. Rhyme), and Age, and maximal random effect structures (random intercepts and slopes of Density Type and Level by subjects and of Age by items). Degrees of freedom for parameter-specific significance tests were estimated using the Kenward-Roger approximation implemented in the pbkrtest package version 0.4-2 (Halekoh & Højsgaard, 2014).

Average naming latencies are shown in Table 3. Overall, older adults were substantially slower to respond than younger adults were ($t(36) = 4.7$, $p < 0.001$), though recall that older adults used a touch-screen to respond whereas younger adults used a mouse, which may also have affected response times. Responses were slower for high phonological neighborhood density words than for low neighborhood density words ($t(36) = 2.2$, $p < 0.05$), consistent with many prior reports of inhibitory effects of phonological neighborhood density in spoken word recognition. This main effect must be interpreted in the context of a statistically significant interaction: across both types of neighborhood density, the effect of density for older adults was significantly larger than for younger adults ($t(36) = 2.4$, $p < 0.05$).

Table 3: Mean (SE) response times.

Age Group	Cohort Density		Rhyme Density	
	High	Low	High	Low
Older	2252	1952	2198	2069
	(132)	(118)	(137)	(123)
Younger	1505	1358	1405	1460
	(118)	(102)	(123)	(108)

Accuracy Accuracy was analyzed using logistic mixed-effects models with crossed random effects of subjects and items (Baayen et al., 2008; Barr et al., 2013; Jaeger, 2008). The full model included fixed effects of Density Level (High vs. Low), Density Type (Cohort vs. Rhyme), and Age, and maximal random effect structures (random intercepts and slopes of Density Type and Level by subjects and of Age by items). The only statistically significant effect was higher accuracy for younger adults compared to older adults ($\chi^2(1) = 4.89$, $p < 0.05$; 95% confidence intervals: Older adults: 79.6% - 89.7%; Younger adults: 86.4% - 94.3%).

Error Types Figure 2 shows the error type totals by Age Group, Density Type (Cohort Density in left panels, Rhyme Density in right panels), and Density Level (High vs. Low). Almost all errors were of one of three types: cohort distractor, rhyme distractor, or undecided (i.e., very few unrelated errors).

A striking pattern of trade-offs between cohort and rhyme distractor errors is clear from the blue and pink segments at the base of each bar stack in Figure 2. Cohort errors appear to be more likely when cohort density is low or when rhyme density is high. Conversely, rhyme errors appear to be more likely when cohort density is high or when rhyme density is low.

To quantify this trade-off directly and to mitigate the sparseness of the individual trial data, we computed the empirical log-odds (e.g., Barr, 2008) of cohort vs. rhyme errors for each participant in each condition (high vs. low cohort density, high vs. low rhyme density), which are plotted in Figure 3.

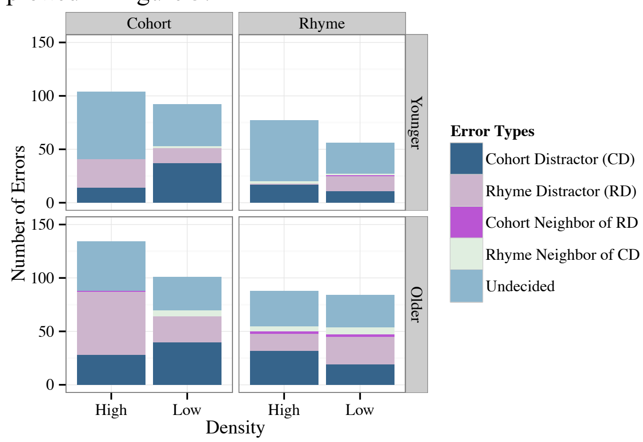

Figure 2: Cumulative total errors by type for younger adults (top panels) and older adults (bottom panels).

Positive values (right of vertical black line) indicate that cohort errors were more likely than rhyme errors; negative values (left of vertical black line) indicate that rhyme errors were more likely than cohort errors. The vertical axis (Condition) refers to density type, the colors indicate density level within each type, and the age groups are shown in separate panels although the pattern is essentially the same for both. These data were analyzed using linear mixed-effects models with fixed effects of age, density type (cohort vs. rhyme) and density level (high vs. low) and random effects of participants and by-participant random slopes of density type and level.

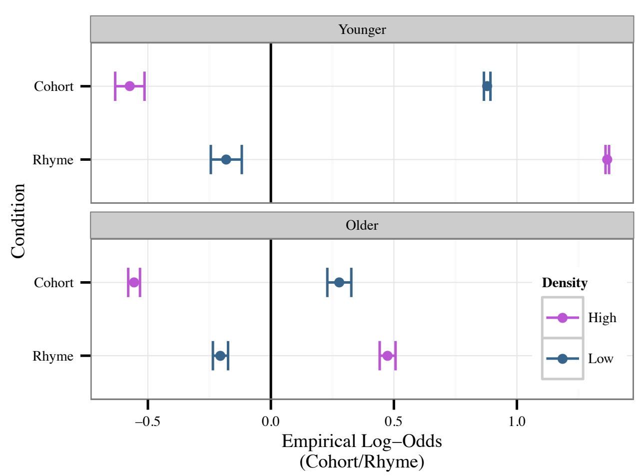

Figure 3: Empirical log-odds of cohort vs. rhyme errors.

There was a significant density type by density level interaction ($\chi^2(1) = 41.97$, $p < 0.0001$), confirming that when cohort density was high, rhyme errors were more common than cohort errors but when cohort density was low, cohort errors were more common than rhyme errors. The pattern for rhyme density was the exact opposite: when rhyme density was high, cohort errors were more common than rhyme errors but when rhyme density was low, rhyme errors were more common than cohort errors. This overall pattern was marginally modulated by age (age by density type by density level interaction: $\chi^2(1) = 3.00$, $p = 0.08$): younger adults showed a marginally larger density type by density level interaction (points in the top panel of Figure 3 are somewhat more widely spaced than points in the bottom panel).

Discussion

The current study evaluated how differences in cohort and rhyme neighborhood density influence the types of errors made by younger and older adults in identifying spoken words presented in moderate noise. We replicate the latency patterns previously reported in the literature, showing overall slower recognition of spoken words from denser neighborhoods (see Luce and colleagues), with a larger effect for older adults (Sommers, 1996). Younger adults were overall more accurate than older adults. The key novel finding was that the relative proportion of cohort vs. rhyme errors was shifted toward cohorts when rhyme density was high, and toward rhymes when cohort density was high. Younger adults showed a marginally larger density type by density level interaction.

The observed error patterns depart from the TRACE model simulations in two important respects. First, overall there were nearly as many rhyme errors as cohort errors, whereas the simulations predicted substantially more cohort errors than rhyme errors. Adding noise increased rhyme error probability in the TRACE model (as we have previously found: Mirman et al., 2011) -- not quite to the level of cohort errors, but a larger amount of noise might be able to accomplish that. However, adding noise also increased unrelated error probability, keeping them at nearly the same level as rhyme errors. In the behavioral data, unrelated errors were very rare, substantially more rare than cohort and rhyme errors. That is, the simulations incorrectly predicted the overall relative rates of cohort, rhyme, and unrelated errors.

Second, the simulations incorrectly predicted that rhyme errors would increase slightly in both high cohort and high rhyme density conditions, and that cohort errors would decrease in the high rhyme density condition. Instead, the behavioral data showed a very symmetric reversal: words with higher rhyme density and words with lower cohort density both elicited increased cohort errors and reduced rhyme errors.

The discrepancy between the behavioral results and the predictions generated by the TRACE model is striking and suggests that in its current form, the model fails to account for the error pattern humans produce in spoken word recognition. However, the model failure must be interpreted with care, as there are a number of reasons why the mismatch between model and human behavior may have occurred (see Magnuson et al., 2012 for discussion of assessing model failures). The TRACE model is a general model of speech perception and spoken word recognition and includes a (simple) system for producing forced-choice responses. It is possible that some properties of our spoken-to-written word matching task modulate lexical activation, competition, or selection in a way that is not captured by the TRACE model.

It is also possible that the simple artificial lexicon used for our preliminary simulations did not capture aspects of the true English lexicon that give rise to these effects, though it is not apparent what those aspects are. Further, the restricted phonemic inventory of the TRACE model makes it impossible (or at least very difficult) to model a realistic English lexicon. For the preliminary simulations reported here, we opted for the tractability of a simple lexicon, but future simulations should consider whether the critical reversal would be produced by a more complex and realistic lexicon.

An alternative possibility is that the single inhibition parameter that determines lexical inhibition in the TRACE model does not fully capture lexical inhibition dynamics. Future simulations will explore alternative formulations of lexical inhibition.

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