Abstract

The evolution of competing lexical categories is simulated within a model in which lexical outputs are organized as sequences of articulatory gestures. When exemplar-based categories compete for assignment and storage of incoming exemplars in a production/storage loop, contrast between categories remains stable, driven by the differences in storage consistency between more contrastive and less contrastive variants. Further, when lexical outputs are biased toward use of previously produced gestures, the set of exemplars in the lexicon evolve to be derived from a small set of contrastive units used in combination, despite the absence of direct selection for contrast at the sub-lexical level.

1 Introduction

The probability of accurate information transmission is dependent on the perceptibility of difference between differently signifying forms, that is, contrast. The possible mechanisms by which contrast arises and is maintained in lexical forms, however, have remained unclear. Many formal grammatical theories of the last century assume that the language faculty is constituted to directly optimize contrast in some way (e.g., Martinet 1955, Flemming 1995), and much computational work also operates within the assumption that contrast between units of form is maintained through some kind of direct monitoring and manipulation of contrast (see e.g., Lindblom 1986, de Boer 2000, and Redford et al. 2001 for examples within phonology). In all of these approaches, contrast is treated as a sui generis property of forms. Here, I will present evidence within an exemplar model of lexical production and perception (Goldinger 2000, Pierrehumbert 2001, 2002) that the fact of a distinction between form-meaning categories themselves, rather than the forms that instantiate them, can indirectly result in contrast preservation between forms through the statistics of assignment of forms to categories.

Exemplar models of categorization propose that categories are composed of many detailed memories of instances, or exemplars, of that category, rather than, for example, a single prototype or a list of category features (for a review, see Nosofsky 1988). As a result, categories can be populated with many differing exemplars of the ‘same’ thing – indeed, the only detail these exemplars must share is the fact of having been placed in the same category. Furthermore, because a percept can be stored as a new member of a category, the contents of categories can evolve with experience. For example, under an exemplar model, the category ‘bird’ will contain many detailed sensory exemplars of actual birds, rather than a single, more abstract element or feature-list, and the kinds of birds that have been recently seen can have an influence on the present behavior of that category.

Within exemplar models of language, a linguistic category consists of many highly detailed exemplars of previously perceived members of that category. An exemplar approach thereby takes the opposite tack relative to standard phonological theory, which has long assumed that lexical categories are highly abstract, and contain only the minimum information necessary to distinguish one category from any other (see e.g. Kenstowicz and Kisseberth 1979). Because lexical categories contain only contrastive detail, matching a perceived utterance with some lexical category cannot rely on non-contrastive phonetic detail that may be present in the utterance.

Conversely, within exemplar models of linguistic category structure, the act of categorizing and storing a percept does not strip that percept all non-contrastive detail (Johnson 1997, Pierrehumbert 2001). As a result, within this model each linguistic category consists of a slowly updating set of many phonetically detailed exemplars of that category.

Evidence also shows that the details of phonetic production of a word can be in turn influenced by the details of recently perceived exemplars of that word (Goldinger 2000). This finding provides evidence for a production-perception feedback loop in adult speakers, in which non-contrastive
phonetic details of what is perceived can be subsequently reflected in the details of what is produced (Pierrehumbert 2001, Oudeyer 2002).

1.1 Overview of the approach

Whenever a system exhibits variation among elements, selection of variants over some criterion, and subsequent reproduction of selected elements, the system will evolve through natural selection on the basis of that criterion. Hence, any factors within the production-perception loop that bias the distribution of forms that are produced, the distribution of forms that are perceived, or the way that percepts are categorized, will result in evolution of category contents. Within the model presented here, lexical categories are populated by exemplars that have been previously categorized as correspondents of that category, and the output of a given category follows a distribution defined in part by the range of exemplars of that category (e.g., Goldinger 1996, 2000, Pierrehumbert 2001, 2002). Outputs are recognized as correspondents of a given category by comparison to exemplars already stored within that category (Johnson et al. 1993, Pierrehumbert 2001, see also Luce and Pisoni 1998). When the loop is closed, such that outputs of a category can be re-stored as new exemplars within that category, any asymmetries in either the form of outputs, or the likelihood of recognition and storage of those outputs, will result in a shift in the contents of that category over time (Pierrehumbert 2001, Wedel 2004). Here, I show simulation results suggesting that contrast between distinct form-meaning pairings can be maintained indirectly through asymmetries in the consistency of categorization of more contrastive, versus less contrastive outputs. Because more contrastive outputs make up a relatively greater proportion of the regularly stored exemplars in a given category than less contrastive outputs, they exercise a greater influence on the evolution of that category. This asymmetry in the statistics of recognition and storage, feeding back into production, results in biased evolution of categories towards greater contrast.

1.2 Contrast preservation through differential categorization.

Within linguistics, the notion that contrast maintenance is an indirect effect of contrast’s effect on a hearer/acquirer’s categorization behavior has been suggested independently by Pierrehumbert (2002) in the context of simulated phonological category evolution, and by Gregory Guy (1996) in the context of the use of production corpora to investigate contrast preservation processes. Guy, for example, argues that data from corpora will always underestimate the true extent of speakers’ failure to produce a given meaningful contrast. Imagine that a transcriber perceives the utterance ‘I cook the chicken’. In the absence of additional information s/he is likely to simply transcribe it as such, even if the speaker actually intended the sentence to be in past tense, but failed to produce the [t] past tense marker with sufficient clarity. Guy notes that language acquirers are no different from transcribers, such that the perception data from which a language learner develops a lexicon and grammar will always be biased towards the more contrastive utterances in the production data set.

1.3 Contrast maintenance as a form of niche specialization.

The mechanism described here for category separation through competition for category members is similar to a mechanism of species divergence first proposed by Darwin (1859, chap. 4) and further developed in recent theoretical research on the effects of resource competition on the distribution of characteristics in a population (e.g., Maxwell and Costanza 1993, Dieckmann and Doebeli 1999). As an example, species divergence driven by competition, also known as niche specialization, is thought to be driven by inequalities in the degree of competition experienced by individuals lying at different points on a distribution of characteristics relating to resource exploitation (Schoener 1974).

As an illustration, imagine that two species of birds that eat the same range of seeds jointly colonize an island. Over time, one likely outcome of the competition between these two species is that they will evolve to specialize on different portions of the seed distribution. For example, one species may develop a bigger beak and preferentially eat bigger seeds, and the other a smaller beak, eating smaller seeds, thereby splitting the resource distribution on the dimension of seed-size. This divergence is proposed to occur because individuals exhibiting intermediate characteristics compete against a larger fraction of the total population, while those with more extreme characteristics have greater individual access to resources, and therefore contribute relatively more progeny to the subsequent generation of their species. As a result of this inequality in reproductive fitness, continued complete overlap in resource preference between the two species is an unstable state over many cycles of selection and reproduction. Instead, the
two species tend to gradually drift apart with regard to some characteristic influencing resource use, such as beak size.

Within the exemplar based model proposed here for contrast maintenance, competing lexical categories are similar to competing species undergoing selection for niche specialization. A given category will be less often matched with a percept that is also close to another category than a percept that is close to no other category. Further, because the matching behavior of a category is determined by its contents, a category will evolve to be more specific for those percepts most consistently identified as members of that category. In this way, categories will tend to evolve to split the available percept space evenly, minimizing regions of overlap (see also Pierrehumbert (2003) for additional discussion of overlap minimization in evolving exemplar-based categories).

2 Modeling contrast maintenance through category competition.

To provide a simple illustration of the phenomenon of category boundary maintenance through patterns of category assignment, I show results of a simple simulation of two interacting, exemplar-based categories, labeled A and B. Each category contains ten numerical exemplars between zero and ten. An example is provided in Figure 1A below.

![Figure 1A](image)

In each round of the simulation, a copy of every numerical exemplar from each category is made, and a small bit of variation is introduced by adding a random value between +/-0.4 to each. Each exemplar-copy is then marked for re-storage in one of the two categories. Crucially, the exemplar-copy is more likely to be marked for storage in the category whose average is closer to its own value. For example, if we start from the categories given in Figure 1A above, a copy of an exemplar with value 4 from Category A will likely be marked for restorage back in Category A, because the exemplar-copy value 4 is closer to the average of Category A than B. On the other hand, a copy of the exemplar with the value 6 from Category A will likely be marked for restorage in Category B. A copy of the exemplar with value 5 from Category A has an equal chance of being marked for restorage in Categories A or B, because its value lies equidistant from the two category averages. At the end of the round, exemplar-copies are stored in the category for which they are marked, and then exemplars are randomly discarded from each category to bring the number of stored exemplars back to ten in each category.

Because the likelihood that a given exemplar-copy will be restored in a category depends on the categories’ averages, the two categories can be said to compete for exemplar-copies on the basis of their own contents. Furthermore, since the average of each category depends on its historical success in competing for exemplars, a feedback loop is closed that ensures that a category will steadily become more like those exemplar-copies it can most successfully compete for.

The simulations shown in Figures 1B and C below begin with each category pre-seeded with 10 exemplars:

<table>
<thead>
<tr>
<th>Category A exemplars</th>
<th>Category B exemplars</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>7</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td>3</td>
<td>6</td>
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<td>4</td>
<td>7</td>
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<td>6</td>
<td>8</td>
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<tr>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>2</td>
<td>8</td>
</tr>
<tr>
<td>5</td>
<td>9</td>
</tr>
<tr>
<td>0</td>
<td>7</td>
</tr>
<tr>
<td>Average: 3</td>
<td>Average: 7</td>
</tr>
</tbody>
</table>

In each round of the simulation, a copy of every numerical exemplar from each category is made, and a small bit of variation is introduced by adding a random value between +/-0.4 to each. Each exemplar-copy increases the variation of exemplars within a category, and increases the rate of change in category contents over simulation cycles.

2 The simulation results shown in Figures 1B and C are not dependent on the particularities of the algorithm used to adjudicate which category an output will be assigned to, provided that an output is more likely to be assigned to the category with contents that are on average closer to that output’s value. A variety of different assignment algorithms with this property were tested, and all produced similar results. The algorithm used for the simulations shown in Figures 1B and C assigned a exemplar-copy to a category with a probability proportional to its relative position between the two category averages, illustrated graphically here for the category averages A:3 and B:7, as shown in Figure 1A:
exemplars, all with the value 5. Figure 1B shows the evolution of the value averages of the two categories over 2000 rounds of production and storage. Note that the averages diverge immediately from their originally shared value of 5, and over the run of the simulation, occasionally approach one another, but never cross.

**Figure 1B.**

![Graph showing evolution with inter-category competition](image)

As a control, Figure 1C shows the results of a similar simulation in which categories do not compete for exemplar-copies, but where exemplar-copies are always re-stored in their category of origin. In this case, the category averages approach and cross one another multiple times, as we expect, given that their pathways through the simulation are independent.

**Figure 1C.**

![Graph showing evolution with no inter-category competition](image)

This difference is robust: when a simulation like that shown in Figure 1B was run 100,000 rounds, there were no crossovers of category averages, while 100,000 rounds of a simulation like that shown in Figure 1C produced 491 crossovers. The failure of the averages to cross in simulations in which categories compete for exemplars is due to the fact that exemplars located between the category averages are less consistently stored in any given category than exemplars lying to one side. This phenomenon is not unlike the mathematical case of a random walk with a wall. If an element begins moving randomly from a given point of origin, its average position will not shift away that origin point over time. However, if we include a wall near the origin, such that the element stops whenever it hits it and then continues moving in some different direction, then the average position of the element will steadily move away from the wall. This obtains because all random movements away from the wall contribute to the average position of the element, but not all movements towards the wall do. With this in mind, consider our two exemplar based categories, A and B, producing variants of exemplars stored in them, which are then restored in the category that they match best. Given that the variants are produced with noise, the category averages should wander around on a random walk over the dimension defining them, as long as all variants from a given category are restored in that same category. When A and B get close together however, noise that moves a variant of A closer to B also raises the chance that the variant will be stored in B, which would prevent that noise from shifting the average of A towards B. However, noise moving a variant of A away from B makes that variant less likely to be stored in B. Hence, when A and B are close, it is as though there is a 'wall' between them, through which extreme variants can tunnel into the other category, thus failing to entirely counterbalance the extreme variants produced by noise on the other, far sides of the categories. Because the average value of categories depend on what has been previously stored, when categories get close enough to begin competing, they tend to shift their averages away from each other until the influences of noise in both directions on the dimension become more nearly equal.

These simulations can be usefully compared to Pierrehumbert’s simulations of merger between exemplar-based phonetic categories under a leniting bias in a similar production/storage loop (2001, 2002). In these simulations, the number of outputs of a category in a given round is proportional to the number of exemplars currently stored there, such that there is a feedback loop between the success of a category in competing for incoming utterances in a given round, and the number of utterances produced from that category in the following round. Exemplars also slowly decay from memory over time, with the result that a category can only maintain itself over the long term through successful competition for incoming utterances. However, because the breadth of the distribution of exemplars in a category tends to
increase as the number of exemplars increases, once a category gains more exemplars than another category competing for a subset of the same utterances, it has a advantage that can snowball, allowing it to eventually absorb the neighboring category, which then ceases to exist. Consequently, in the absence of some mechanism to maintain contrast between categories, competition between categories for incoming utterances makes the long-term co-existence of competing categories inherently unstable. The absorption of one phonetic category by another is a common occurrence in language change, as for example in the absorption of [ɔ] into [a] in western dialects of American English.

In contrast, within the simulations presented in Figure 1 above, the number of productions from each category in a given round remains constant, without regard to how well that category has competed for outputs in previous rounds. Because the existence of each category is not linked to its historical success in competing for outputs, categories will remain distinct even if at some point they have identical contents, as in the starting point of the simulations shown in Figure 1B and C. This behavior may be appropriate for lexical categories, as opposed to the phonetic categories modeled by Pierrehumbert, because the former can be anchored in physical and social experience outside the linguistic system. As such, distinctions in meanings may remain intact, even if corresponding forms merge, i.e., become homophonous. For example, if the lexical form for the sound-meaning category ‘thirteen’ were to change to become homophonous with the similar lexical form for the sound-meaning category ‘thirty’, we would presumably not find ourselves significantly less interested in talking about the concept 13 than we were before. The same cannot be said concerning the merger of sub-morphemic categories, as they have no independent correspondent in meaning; if two originally distinct sounds become identical, there is nothing left to distinguish them.

If we accept then that the notion of contrast only has functional substance in the context of an actual form-meaning pairing, we might expect a contrast-supporting mechanism to act primarily on actual form-meaning categories, rather than on the sub-morphemic categories that they are composed of. Competition between lexical categories is a candidate mechanism for contrast maintenance that has this property.

3 The interaction of contrast maintenance and motor consolidation.

Given the hypothesis that contrast maintenance is driven through category competition between form-meaning pairings, we then need an account for the observation that morphemes themselves do not appear to be the minimal unit of contrast in phonological systems. Rather, we find that phonological systems can be described in terms of sub-morphemic contrastive features and featural groupings. In the simulations presented in this section, I explore the hypothesis that contrastive, sub-morphemic units can arise indirectly through category competition for the larger lexical forms of which they are a part.

The simulation architecture employed here consists of a single speaker/hearer pair, each equipped with small lexicons of categories populated with stored exemplars. In a given round, one of the pair utters the contents of its lexicon to the other, which attempts to categorize and store each utterance by comparing it to the exemplars stored in its lexicon. In the next round, the roles reverse. The complexity of the simulation architecture is purposely kept as low as possible to enable us to better assess the hypothesis that the simulation results are due to patterns of information flow in the system, rather than particular details of implementation.

At the start of a simulation, each speaker/hearer is provided with a starting lexicon comprising a number of categories, each containing six exemplars. Exemplars are structured as an ordered sequence of gestural targets (Browman and Goldstein 1990; see also Oudeyer 2002). Two articulators are provided in the simulation, labeled X and Y, where X can vary within a target range from 0.00 – 0.30, and Y from 0.00 – 0.10. Each exemplar consists of four ordered pairs (‘segments’) of X and Y target values, as for example in the possible 4-segment exemplar shown below:

<table>
<thead>
<tr>
<th>Segment Position</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>X target value:</td>
<td>.10</td>
<td>.25</td>
<td>.07</td>
<td>.20</td>
</tr>
<tr>
<td>Y target value:</td>
<td>.05</td>
<td>.00</td>
<td>.02</td>
<td>.10</td>
</tr>
</tbody>
</table>

A tight linkage between acoustic/perceptual and articulatory maps is assumed (e.g., Oudeyer 2002 and references therein), and because structure potentially emerging from the interactions between perceptual and articulatory mappings is not at issue here, recorded exemplars and outputs of
In the model, production are both encoded in the same units for computational simplicity.

Unless otherwise specified, at the beginning of each simulation the lexicons of each speaker/hearer are seeded with fully randomized exemplars. In a given round, one of the pair produces three randomly chosen exemplars from each of its lexical categories for the other, which categorizes and stores the produced outputs by comparison to the stored contents of its own lexical categories.

Production proceeds by selecting a single random exemplar from a category, and then assembling a corresponding output. In modeling assembly of production outputs, the simulation architecture incorporates the finding that practiced gestural targets serve as attractors in motor planning and execution (or stated another way, that once a movement is practiced a certain way, future movements tend to recapitulate the practiced gesture if possible, e.g., Shadmehr and Bashers-Krug 1997 and references therein; for additional discussion in the context of phonology, see also Saltzman and Munhall 1989, Brownman and Goldstein 1990, Plunkett and Marchman 1991, Bybee 2001, Ussishkin and Wedel 2003). The neural mechanism for the consolidation of motor patterns is not under study in these simulations, and so for computational simplicity it is simply stipulated. Simulations that model neural mechanisms for the development and action of attractors in developing systems can be found in e.g., Guenther and Gjaja (1996) and Oudeyer (2002). There is also evidence that percepts are warped toward the center of categories (Kuhl 1991), which in the context of a production-perception feedback loop would contribute an additional pressure toward consolidation of motor targets. Warping at the level of perception was not included in this model.

To model the warping of motor targets toward more highly practiced output, each speaker/hearer retains a record of what articulatory targets have been produced over the previous six rounds. An output target value for each target value recorded in the chosen exemplar is established by comparing the reference exemplar target value to every target value recently produced by that articulator. Recently produced target values are activated in Gaussian proportion to their proximity to the reference exemplar target value3. The probability that a particular target value will be chosen is directly proportional to its activation with respect to the corresponding position in the exemplar under production.

For example, if the particular target value recorded in the exemplar chosen as the basis for production has been produced many cycles of production and perception, the result is a steady tendency to consolidate output target patterns over time.

Finally, each production target is produced with Gaussian noise: in the simulations shown here, the variance in the noise distribution was such that each intended target had a 10% chance of being modified +/- .01 on the target scale. Up to a point, increases in the breadth and amplitude of the noise distribution simply increase the rate at which the system explores new states; beyond this point, the system begins to lose stability as production events become increasingly random.

Category assignment on the part of the hearer proceeds by comparing the speaker output to all exemplars stored in the hearer’s lexicon. Whether a hearer exemplar will be counted as matching the speaker’s output is assessed by comparing each target value in the output to the target value at the corresponding position in the stored exemplar, where the probability of being counted as a match follows a normal distribution with a probability of 1 at equal target values and a standard deviation of 0.03 on the scale of possible target values. As a result, for example, if an output target value is +/- .05 from the comparison exemplar target value, it still has about a 30% chance of being judged a match. For the output as a whole to be counted as a match to a given exemplar, each of their corresponding target values must have been judged a match individually.

After all output-exemplar matches have been determined within the hearer’s lexicon, the output is assigned to and stored in a single lexical

where $n$ is the number of times that the target value under consideration has been produced in the previous six rounds, $a$ is the target value, and $b$ is the reference target value in the exemplar under current production. There is nothing crucial about the details of this algorithm, beyond the fact that activation is related to similarity to the exemplar value and frequency of previous use. Substitution of other formulas that produce a similar relation between activation, similarity and frequency produces similar results.
category, where the probability of category assignment is proportional to the square of the number of matching exemplars in each category. For example, if an output is successfully matched to 2 exemplars in lexical category A, and 1 exemplar in B, it is four times as likely to be assigned to A as B. This matching and assignment procedure is intended to approximate probabilistic activation and competition between lexical entries in lexical access, culminating in a unique output-category match, as in many models of lexical access (e.g., McLeodland and Elman 1986, Norris 1994, Luce and Pisoni 1998). If an output lies an equivalent distance between two categories (i.e., it is matched to equal numbers of exemplars in the two categories), it has an equal chance of assignment to each category. Only if a speaker output has been matched to no exemplar in the hearer’s lexicon will it fail to be assigned to some category. When an output is assigned to a category and stored there as a new exemplar, a randomly chosen exemplar from a previous round is discarded.

To summarize, in each round, one speaker/hearer produces utterances for the other, each based on an exemplar from a lexical category. An utterance is not necessarily identical to the exemplar it is based on, because (i) output target values tend to be warped toward similar, frequent output targets that have been previously produced, and (ii) random noise may be added to any target value, producing a small additional variation. The hearer in each round assigns an utterance to one of its lexical categories by comparing the utterance to all the exemplars in its lexicon. An utterance is more likely to be assigned to a lexical category that has many exemplars that are similar to the utterance. Crucially, since an utterance can only be assigned to one category, utterance-types that are similar to exemplars in multiple categories will be assigned to any given category less frequently than an exemplar that is similar to the exemplars in only one category.

3.1 Evolution of lexical categories in the absence of inter-category competition.

The tendency to warp output target values toward those values that have been produced before results in a steady reversion to mean target values over the course of the simulation, counteracting the dispersive effects of noise in production (Wedel 2004). This can be seen in a control simulation in which category competition in lexical access is disabled by providing the speaker/hearers with an additional channel of communication, such that each speaker output is stored directly in the corresponding hearer category without regard to similarity any other category’s contents.

There are 96 distinct X and Y target values recorded in the lexicon at any given time, because the lexicon contains four categories, each containing six exemplars, each made up of four X-Y segments. Figure 2A shows the distribution of X target values within the lexicon of one of the speaker/hearers at the beginning of a simulation.

Because all target values have been randomized at the start of the simulation, the distribution of X target values shown in Figure 2A, and Y values in

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4 Varying the scaling between relative number of matches and probability of category assignment within a reasonable range does not significantly change the behavior of the simulation. As the exponent is raised, variation in category assignment decreases, resulting in slower evolution of the system. As the exponent is lowered on the other hand, category assignment becomes less dependent on the relative goodness of match.

5 Reversion to the mean in production can also be ensured by selecting multiple exemplars from a category and averaging them in production (e.g., Pierrehumbert 2001). The category-sharpening effect of motor consolidation renders this unnecessary in this model.
Figure 2B, extends across the available range, with no clear pattern. After 1000 rounds in the absence of category competition, however, we see that the distribution of X and Y target values narrows considerably, as shown in Figures 3A and B below for the same speaker/hearer.

Figure 3A. X values at Round 1000.

Figure 3B. Y values at Round 1000.

While the X and Y target values are well-distributed across the possible range at the beginning of the simulation, steady feedback pressure for output target values to become more alike results in the evolution of a system with only one possible target value for each articulator. This can be seen in Figure 3A, where the X target values have consolidated around a value of .14, and the Y values have consolidated around .02.

Recall that the uncertainty in target value matching in the process of output assignment to a category is such that values within .03 of each other are quite likely to count as ‘the same’. Consequently, the lexicon that has evolved without category competition has, functionally speaking, only one X and one Y target value as far as contrast is concerned. As a result, all four lexical categories contain essentially the same set of exemplars. Figure 3C shows the median (i.e., most frequent) target values for each position within each of the four lexical categories at round 1000 in this simulation. For example, throughout Figure 2C, the most common X value is reported as ‘.14’. Comparison with Figure 2B shows that this is in fact the most common X target value in the lexicon. The lexicon of the other speaker-hearer is essentially the same.

Figure 3C. Median target values: Round 1000.

<table>
<thead>
<tr>
<th>Segment Position</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Category</strong></td>
<td></td>
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3.2 Inter-category competition supports maintenance of contrast.

When category competition is reintroduced, however, something quite different happens: although target values still show significant consolidation over the course of the simulation, sufficient distinctions remain to preserve contrast between lexical categories. Figure 4A shows the range of X target values, and 4B a summary of the lexicon at round 1000 of a simulation that incorporates category competition.

Figure 4A. X values at Round 1000.

In this simulation, at 1000 rounds X target value consolidation has resulted in two contrastive
targets value groupings rather than one, centered
around .03 and .20. Y target value consolidation
has proceeded to the limit, resulting in a single
target value grouping, centered on .06 (not shown).

Figure 4B. Median target values: Round 1000.

<table>
<thead>
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<th>Segment</th>
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<tbody>
<tr>
<td></td>
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<tr>
<td>Category</td>
<td>X: .20</td>
</tr>
<tr>
<td>A</td>
<td>Y: .06</td>
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<tr>
<td>Category</td>
<td>B: .03</td>
</tr>
<tr>
<td></td>
<td>Y: .06</td>
</tr>
<tr>
<td>Category</td>
<td>C: .03</td>
</tr>
<tr>
<td></td>
<td>Y: .05</td>
</tr>
<tr>
<td>Category</td>
<td>D: .20</td>
</tr>
<tr>
<td></td>
<td>Y: .06</td>
</tr>
</tbody>
</table>

In Figure 4B, equivalent ‘segments’ are shaded
equivalently. Note that although there are only two
costive target groupings in the lexicon shown
in Figure 4B, every lexical category is distinct
from every other by virtue of differing distribution
and position of the two target groupings.

This represents an example of selection at one
level indirectly resulting in change at another, as in
biological evolution when, for example, selection
at the level of the individual results in change at
the level of the gene. Here, we see that direct
selection for contrast at the level of the entire
output form can result in indirect selection for
contrast at a smaller, sub-lexical level.

Note that the development of contrastive lexical
forms in distinct categories is not dependent on
less contrastive variants being less often stored. In
the numerical simulations described above in
section 2, every output was stored in a category. In
the simulations described in this section however,
every variant form was stored in some category,

7 The lexicon of the other speaker/hearer is the
same, with the caveat that each category label is
not necessarily matched with the same ‘word’,
because no mechanism for synchronization is made
available to the pair. However, if the speaker in a
given round is allowed to ‘point’ to the intended
category in a small proportion (e.g. 2%) of its
communications, so that the hearer can store the
utterance directly the corresponding category,
then the pair do develop parallel category-word
lexicons. This low-level ‘deixis’ was not included
in the simulations shown here in the spirit of
keeping information-flow in the system as simple
as possible.

provided it could be matched to at least one
exemplar. A variant lying between two categories
has therefore a greater chance of being matched
and stored than a variant that lies an equivalent
distance away from a single category, even though
the latter is functionally more contrastive. This
generous assignment and storage procedure was
chosen to make it less likely that the development
and maintenance of contrast within the simulations
could be due to differential rates of storage, as
opposed to differential consistency of storage.
Previous work (Wedel 2004) has shown that in
similar simulations in which outputs matching
multiple categories were at a disadvantage in
storage efficiency relative to those matching just
one category, development and maintenance of
contrast was yet more robust than in the
simulations shown here. Phenomena such as the
neighborhood density effect in lexical access
indicate that outputs activating multiple lexical
categories may in fact be at a disadvantage in
recognition (reviewed in Luce and Pisoni 1998).
However, the simulation results presented here
suggest that in addition to the effect of any
disadvantage in storage of poorly contrastive
forms, lower storage consistency of less
contrastive forms alone can contribute to contrast
maintenance between lexical categories.

Two contrasts are the minimum necessary for
lexical contrast in a four-category, four-segment
exemplar lexicon as modeled in the simulations
illustrated in Figures 3 and 4. This represents an
optimum between pressure to use the minimum
number of distinct target values, and pressure to
maintain category contrast. Starting from fully
randomized seed exemplars however, not all
simulations reach this optimum within a few
thousand rounds, because of randomness in how
target groupings and positions within exemplars
are negotiated in the first few hundred rounds. If
lexical category contents develop that don’t allow
some target value differences to change without
those lexical categories losing contrast, then the
system may have a difficult time finding pathways
to further reducing the number of target value
differences. The simulations shown in Figures 5, 6
and 7 below illustrate this phenomenon.

Figures 5 and 6 illustrate the evolution of
another four-category lexicon at 800 and 2000
rounds, respectively, starting again from a fully
randomized exemplar set at round 0. Figures 5A
and B show the X and Y target values that have
been reached at 800 rounds, while Figure 5C
shows the corresponding consensus target values
within the four categories.
By 800 rounds, the initially randomly distributed X and Y target values recorded in the lexicon have coalesced into three and two peaks, respectively. Figure 4C shows the distribution of these values within exemplars across the four categories in the lexicon. Values shown represent the median target values from each category; equivalent segments are shaded equivalently.

Figure 5C. Consensus target values: Round 800.

<table>
<thead>
<tr>
<th>Segment Position</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Category</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>X:</td>
<td>.13</td>
<td>.27</td>
<td>.02</td>
</tr>
<tr>
<td></td>
<td>Y:</td>
<td>.02</td>
<td>.10</td>
<td>.02</td>
</tr>
<tr>
<td>B</td>
<td>X:</td>
<td>.01</td>
<td>.27</td>
<td>.27</td>
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<tr>
<td></td>
<td>Y:</td>
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<td>C</td>
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<tr>
<td></td>
<td>Y:</td>
<td>.02</td>
<td>.09</td>
<td>.01</td>
</tr>
<tr>
<td>D</td>
<td>X:</td>
<td>.13</td>
<td>.02</td>
<td>.01</td>
</tr>
<tr>
<td></td>
<td>Y:</td>
<td>.02</td>
<td>.02</td>
<td>.10</td>
</tr>
</tbody>
</table>

Again, we see that all four categories have contrastive contents, which in this simulation at round 800 are derived from five segment types, each containing one of three possible X values, and one of two possible Y values.

Figures 6A-C show the state of the simulation run 1200 further cycles, out to 2000 rounds. Note that while the Y values have remained stable, the X-value peak at [0.01] apparent at round 800 has disappeared, absorbed into the peak at [0.14]. Figures 6C shows the distribution of these target value peaks within the evolving lexicon.
Comparison of Figures 5C and 6C shows that by round 2000, the number of contrastive segment types has been reduced from five to three, but contrast between the four lexical categories is maintained. This result accounts for how the merger of the X [.01] and [.14] target values could so readily take place, in that for no lexical category was the contrast provided by the apposition of X target values of [.01] and [.14] crucial to maintaining lexical contrast.

The same cannot be said of the contrast between the Y target values [.01] and [.09]. Although the [.09] target is not necessary for lexical contrast in the lexical categories A and B, if the [.09] and [.01] targets merged across the entire lexicon, categories C and D would no longer be distinct. Competition between categories C and D can explain why these two targets do not merge in these lexical categories, but we might then ask why the [.09] and [.01] targets don’t go ahead and merge in lexical categories A and B, where they are not needed. The answer lies in the fact that in this simulation, similar target values, even though they may be recorded in separate lexical entries, strongly influence one another in production. This mutual influence of similar target value outputs on each other makes them tend to behave as a single production unit. Because of this linkage, a potential global merger between two target values can be inhibited even if they are required for contrast in only a subset of the lexicon. This effect is illustrated in the simulations presented below.

### 3.3 Local lexical contrast patterns can influence the evolution of global sub-lexical contrasts.

The following simulations show that when target values are bound together by their similarity in a single unit of motor production, a given target value that is required to maintain contrast between two categories can support the persistence of that target value elsewhere, even if it would otherwise tend to merge with another nearby target value. To illustrate this phenomenon, two simulations were run starting from two distinct, non-random lexicons, shown in Figures 7A and B. Each simulation uses eight lexical categories, pre-seeded with exemplars consisting of three X target values (0.30, 0.15, and 0.05), and one Y value 0.00. The X [.05] value (found only in the final, shaded positions of categories A, C, and E) is in the minority relative to the [.15] target value, and therefore will be under pressure from motor consolidation to merge with it.

In the starting lexicon shown in Figure 7A, the minority X value [.05] can increase and merge with the more frequent X value [.15] without any loss of category contrast, because categories A, C and E differ from every other category by at least two positions. (The identical Y values across the lexicons in Figures 7A and B are irrelevant to contrast, and so are omitted for clarity).

**Figure 7A. Starting target values: Round 0.**

<table>
<thead>
<tr>
<th>Category</th>
<th>X-1</th>
<th>X-2</th>
<th>X-3</th>
<th>X-4</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>.15</td>
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<td>.30</td>
<td>.05</td>
</tr>
<tr>
<td>B</td>
<td>.15</td>
<td>.30</td>
<td>.15</td>
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<td>C</td>
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<td>D</td>
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<td>.05</td>
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<tr>
<td>E</td>
<td>.30</td>
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<td>.15</td>
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<td>G</td>
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<tr>
<td>H</td>
<td>.15</td>
<td>.30</td>
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</tbody>
</table>

For example, if the X target value [.05] in category A were to increase to [.15], category A would still remain distinct from the closest category B, because B would still differ from A in other positions. As expected, when simulations are run with this starting lexicon, the minority [.05] values do in fact quickly merge with the more frequent [.15] value. In ten independent runs of the simulation with this starting lexicon, merger always took place within 400 rounds.

Figure 7B shows a starting lexicon that is nearly identical, except that in categories B and D, the target values in two positions have been switched. Arrows and shading indicate which positions have been exchanged to convert the lexicon shown in 7A to that in 7B. The starting lexicons shown in Figures 7A and 7B therefore have the same relative numbers of [.30], [.15] and [.05] X target values; it is only their distribution in the lexicon that is different. Although the switch does not change the relative frequencies of X target values, it does change their relative functional load: in the lexicon shown in 7B, if the [.05] target values of categories A and C increase to [.15], these categories will lose contrast with categories B and D, respectively, because all positions would then become identical. The [.05] target value of category E can still merge with [.15] with no loss of category contrast.
In ten independent simulations starting with the lexicon shown in Figure 7B, run out to 1000 rounds, the [.05] target values of categories A and C did not ever merge with the [.15] target value, as expected. Interestingly, in eight of these runs, the [.05] target value of category E also failed to merge with [.15], even though this value was not required for contrast in category E. Recall that merger quickly occurred in this category when the [.05] target value was not required for contrast in categories A and C, as in the lexicon shown in 7A. The difference in evolution of these lexicons illustrates that within this simulation architecture, category competition resting on a given target value in one part of the lexicon can stabilize that target value throughout the lexicon, even in regions of the lexicon where its functional load is low.

As suggested by the simulation architecture, this effect is dependent on the details of frequency: *ceteris paribus*, the ratio of contrast-bearing to non-contrast bearing instances of a target value influences the probability of merger (see Labov (1994:328ff) for similar arguments on mergers in vowel systems). In the lexicon in 7B for example, two out of the three instances of the target value [.05] bore sole responsibility for maintaining the contrast of lexical category of which they were a part. If the lexicon is altered such that only one of the three instances of that target value bears responsibility for contrast in a lexical category, then in a significant number of runs, the other two instances of the [.05] value do in fact merge with [.15], and in the process drag the one contrast-bearing [.05] value with them, despite the fact that this produces a pair of ‘homophonic’ categories in the lexicon (not shown).

Within this simulation architecture, the attractor formed by identical target values in output assembly is stronger than the statistical force pressing different category contents to diverge in storage, such that once homophonic categories form, they have not yet been observed to split and regain contrast. This appears to be largely true for actual lexical categories as well (but see Yaeger-Dror 1996, and Jurafsky et al. 1996 for evidence that highly frequent homophonic categories may be able to split under some circumstances).

4 Discussion

The simulation results described here illustrate that competition between categories for form variants in a production/storage loop indirectly supports maintenance of contrast across form-category pairs. As suggested by Guy (1996) and Pierrehumbert (2002) in linguistics, as well as by theoretical work in niche specialization in evolutionary biology (e.g., Schoener 1974, Deickmann and Doebeli 1999), this phenomenon rests on unequal partitioning of variants across self-reproducing categories: highly contrastive variants contribute to single categories more often than less contrastive variants, with the result that the lexicon evolves to reflect the more contrastive variants.

Consistent with this line of reasoning, speakers have been shown to produce more contrastive phonetic detail when producing words in high-density lexical neighborhoods (e.g., Goldinger and Summers 1989, Wright 1996, Brown 2002), which could be a reflection of the distribution of phonetic details stored in the lexical categories in high density neighborhoods. However, it should be noted that in the context of a production-perception feedback loop, any and all properties of language-use favoring production or perception of contrastive forms will favor contrast maintenance between lexical categories. The results of these simulations should therefore be taken as evidence that competition between lexical categories constitutes a plausible mechanism supporting contrast maintenance, but not necessarily the only one.

These simulations also bear on the question of how contrast between form-meaning categories relates to contrast between the sublexical, phonetic categories that form the building blocks of lexical categories. The structure of exemplars in these simulations models the lexical form as a set of temporally ordered articulatory gestures (Browman and Goldstein 1989). This structure allows, but would not dictate, the evolution of a combinatorial system in which simulated gestures or gestural groupings are reused in distinct lexical forms. However, evidence strongly suggests that practice of coordinated muscular gestures results in consolidation into larger-scale motor programs, which then serve as attractors in motor planning.

Figure 7B. Starting target values: Round 0.

<table>
<thead>
<tr>
<th>Category</th>
<th>X-1</th>
<th>X-2</th>
<th>X-3</th>
<th>X-4</th>
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<tr>
<td>A:</td>
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</table>
and execution (Shadmehr and Bakers-Krug 1997 and references therein). To model this effect in output assembly, target values were warped towards those values that had been frequently produced in the speaker’s recent history. The resulting tendency to minimize target value differences conflicts with the statistical reward enjoyed by more contrastive forms, resulting in an optimization in which lexical entries evolve to contain contrastive exemplars, which are themselves composed of a small number of units repeated in forms throughout the lexicon. Rather than being stipulated anywhere in the system, the development of a small set of contrastive sub-lexical units evolves indirectly through competition between the actual form-category pairs that contain them. Interestingly, as we saw in the simulations described in conjunction with Figures 7A and B, the tight association of similar target values as ‘motor units’ allows a functionally unnecessary contrast to persist in a given lexical category, if that contrast is functionally required in another.

The potential influence of contrast on sound change suggested by these results is supported by at least two well-described phonological phenomena. First, certain exceptions to otherwise regular sound change, sometimes referred to as ‘anti-homophony effects’, occur precisely where sound change would give rise to loss of a paradigmatic contrast. In this case, data from unrelated languages supports a cross-linguistic tendency for contrastive exemplars to be preferred exactly where lexical categories are in greatest competition (Blevins (to appear), Gessner and Hansson 2004). Mecklenburg German (Kiparsky 1982) provides an example, in which final unstressed schwa can be deleted from nouns, except when the schwa is the sole marker of plurality:

i. [gast] ~ [gesta] → [gast] ~ [gest] ‘guest(s)’
   but:
ii. [sper] ~ [spera] × [sper] ~ [sper] ‘javelin(s)’

A second finding is that rare phonological contrasts (e.g., a three-way contrast in vowel or consonant length, or a three-way contrast in nasalization) are not randomly distributed in the lexicon. Rather, in languages making use of rare contrasts, these contrasts are often the sole exponents of contrastive morphological features, and hence are only contrastive in contexts of lexical competition (Blevins 2004, chapter 8). The simulations presented here can account for both these findings in terms of contrast-driven statistical selection of exemplars at category extremes. In the case of anti-homophony, this selection inhibits the progression of a sound change in limited contexts where morphemes strongly compete. In the case of rare contrasts, selection inhibits expected mergers in limited contexts where that contrast is the sole exponent of contrast.

Finally, the results of these simulations contribute to an ongoing discussion of the divergent relationship between lexical frequency and morphological, versus phonological ‘regularity’ (see e.g., Pierrehumbert 2002). The well-known tendency to morphological irregularity in high-frequency forms can be explained as an effect of frequency on lexical access: the higher resting activation level of frequent forms should allow them to be identified holistically, rather than through identification of their individually contrastive morphemes. Similarly then, we might expect that highly frequent words should be able to evolve to be phonologically exceptional, for example by resisting a sound change sweeping through the rest of the lexicon, or developing an otherwise unattested phone. However, in general we find just the opposite: highly frequent forms do conform to sound changes initiated elsewhere, tend to be the most lenited, and tend as well to comprise more common sounds (see Bybee 2002 and Pierrehumbert 2002 for discussion). This can be explained within a model in which phonological, but not morphological categories tend to be coextensive with motor units, if we assume a tendency toward effort minimization in production. Ceteris paribus, highly practiced motor scores are deployed more rapidly and accurately than less practiced motor scores (Shadmehr and Bakers-Krug 1997 and references therein), and so we can consider lexical evolution toward use of more common motor scores a language-specific form of lenition. If a sound change sweeps through most of a lexicon altering one motor score into another, highly frequent forms might also be expected to shift away from the original, now infrequent motor score to the new highly frequent one, not because they must, but because their high frequency encourages lenition (reviewed in Bybee 2001). Preliminary simulation results exploring the interaction of exemplar frequency and warping toward frequent target values support this hypothesis.

5 Acknowledgements

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References


