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AGAINST UNDERSPECIFICATION IN SPEECH ERRORS*

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This paper argues against the use of phonological underspecification in feature matrices on the basis of speech error data. Stemberger 1991 argues that phonological underspecification influences the similarity of phonemes. He claims underspecified features do not count toward similarity, based on an analysis of phoneme confusions in a naturally occurring speech error corpus. Using the same corpus, I show that a similarity metric that does not employ underspecification provides a better account of the data. This similarity metric, originally proposed in Frisch, Broe, & Pierrehumbert 1995, is sensitive to featural redundancy but does not omit redundant features. In this metric, redundant features contribute less toward similarity than contrastive features. These results show that redundant features play a role in predicting speech errors, and thus that phonological representations must encode redundancy and not exclude it.

1. Introduction

Traditional approaches to feature specification have distinguished distinctive features from redundant features. Broe (1993, chapter 4) provides an extensive review of the evolution in the treatment of redundancy in generative phonology. We can draw from his discussion the following two conclusions. First, some phonological processes have been shown to be sensitive to the status of a feature as distinctive or redundant. Thus, redundancy must be encoded in the phonological representation. Second, redundant features are traditionally encoded by omission of the feature specifications in underlying representations (so-called UNDERSPECIFICATION, Kiparsky 1982; Archangeli 1984, 1988). Broe accepts that redundancy must be encoded in phonological representations, but rejects the method of encoding redundancy using underspecification. The use of feature blanks to encode redundancy creates a number of formal problems for phonology (Broe 1993:193-209). Broe proposes STRUCTURED SPECIFICATION, where the redundancy of features is encoded hierarchically, and redundant features are not omitted from the phonological representation.

In addition to its use in formal linguistic theory, underspecification has been applied to problems in speech production (Stemberger 1991a, 1991b, 1992, 1993), speech perception (Lahiri & Marslen-Wilson 1991, 1992), and language acquisition (Dinnsen 1993). In this paper, I propose an alternative analysis to Stemberger 1991b using structured specification (Broe 1993). In particular, Stemberger 1991b proposed that underspecified features have less influence on the similarity of consonants, and hence speech error rates, since underspecified features are blanks during early portions of the derivation. However, he did not consider the effect that underspecification would have on similarity outside of the small number of minimal contrasts that he examined. I demonstrate that computing similarity using structured specification provides a more accurate prediction of error rate than measures of similarity based on underspecified feature matrices, when the entire corpus of phonological segment errors are examined.

1.1 Underspecification

Underspecification refers to the practice of leaving blanks in feature matrices which are filled in during the course of the phonological derivation. There are two types of underspecification which are generally practiced: CONTRASTIVE UNDERSPECIFICATION and RADICAL UNDERSPECIFICATION. In contrastive underspecification (Steriade 1987), non-contrastive features are left out of the feature matrix. For example, the [+voice] feature of sonorant consonants in English is predictable, since all sonorants are voiced. Thus, in contrastive underspecification, stops and fricatives are marked as [±voice] but sonorants would be underspecified. A redundancy rule [+son] → [+voice] applies during the phonological derivation. Some phonological processes, such as devoicing coda consonants in German, are proposed to apply before the redundant voicing feature is filled in, with the result that coda sonorants do not devoice in German.

Radical underspecification (Archangeli 1988) proposes that one value for each feature is considered the default and is always left blank in underlying representation. For example, [-voice] is considered to be the unmarked value of voicing in obstruents, so voiceless obstruents are underspecified for voicing. In radical underspecification, the [-voice] specification is inserted by a default rule which marks any consonant without a voicing feature as [-voice]. As with contrastive underspecification, predictable features are also left blank, so [+voice] in sonorants is also underspecified and filled in by a redundancy rule.

1.2 Structured specification

In structured specification, feature blanks are used solely to represent that a segment is undefined for a particular feature. For example, [±ant] is irrelevant for labials and so is not specified. Redundancy is encoded in the REDUNDANCY HIERARCHY. Properties which were formerly encoded by blanks are differentiated formally in the hierarchy.

Given a segment inventory and a set of features, the redundancy hierarchy for that set of segments given that feature set can be unambiguously determined. The hierarchy is based on the partial ordering of natural classes of segments given a featural representation. The natural classes are ordered by set containment: larger natural classes contain smaller ones. I exemplify the algorithm with a simple case, the three vowel inventory. The interested reader should consult Broe 1993 for a more rigorous treatment of the set theoretic and graph theoretic ideas employed here. Consider, for example, feature specifications for a three vowel inventory {a, i, u}.[1]

(1)

	/a/	/i/	/u/
[high]		+	+
[low]	+		
[front]		+	
[back]	+		+

To construct a redundancy hierarchy for the three vowel inventory, we first consider the set of natural classes which can be denoted by the feature matrix in (1). There are 4 feature values, so there are $2^4 = 16$ possible conjunctions of features. Each feature conjunction, with its corresponding natural class, is given in (2). The symbol ∅ denotes the empty set, which is the natural class created by an incompatible conjunction of features. Out of the 16 possible conjunctions of features, there are 7 distinct sets of segments. These are the natural classes. They are {a, i, u}, {a, u}, {i, u}, {a}, {i}, {u}, ∅. These 7 sets are partially ordered by the set containment relationships given in (3).

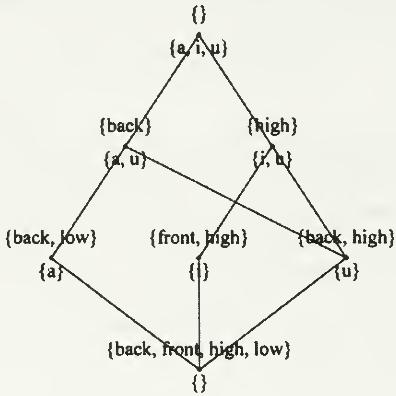
(2) {[]} = {a, i, u}
{[+high]} = {i, u}
{[+low]} = {a}
{[+front]} = {i}
{[+back]} = {a, u}
{[+high]&[+low]} = ∅
{[+high]&[+front]} = {i}
{[+high]&[+back]} = {u}
{[+low]&[+front]} = ∅
{[+low]&[+back]} = {a}
{[+front]&[+back]} = ∅
{[+high]&[+low]&[+front]} = ∅
{[+high]&[+low]&[+back]} = ∅
{[+high]&[+front]&[+back]} = ∅
{[+low]&[+front]&[+back]} = ∅
{[+high]&[+low]&[+front]&[+back]}= ∅

(3) {a, i, u} ⊇ {a, u}, {i, u};
{a, u} ⊇ {a}, {u};
{i, u} ⊇ {i}, {u};
{a}, {i}, {u} ⊇ ∅

Note that not all set containment relationships are given in (3). Relationships which can be deduced by transitivity are omitted. For example, {a, i, u} ⊇ {u}, which can be deduced from {a, i, u} ⊇ {a, u} and {a, u} ⊇ {u}.

A LATTICE is a partial ordering of the natural classes of segments which are possible given a featural representation. Figure 1 shows the lattice of the three vowel inventory graphically. Each node in the lattice is a natural class, and the set of features and segments which the node denotes are shown above and below the node, respectively. Nodes are ordered from top to bottom by size. The top node of the lattice represents the entire inventory, and the bottom node is the empty set. The row of nodes just above the bottom are the natural classes containing the individual segments. The features which denote these nodes are the features of the segments. Lines connecting nodes indicate set containment. Note that, as in (3), not all set containment relationships are indicated by lines, those that can be deduced by transitivity are excluded.

Figure 1: Lattice of the three vowel inventory.



There is a dualism between sets of segments (natural classes) and sets of features in the lattice. The hierarchical set containment relationship between the natural classes corresponds to an inheritance relation for the features that define those natural classes. For example, the natural class {u} is {[+back]&[+high]}. It is contained by the natural class {i, u}, which is {[+high]} and by the natural class {a, u} which is {[+back]}. The natural class {u} inherits the feature [+back] from the natural class {a, u} and it inherits [+high] from {i, u}. Through set containment and feature inheritance, the lattice represents redundancy structurally. For example, {[+front]} = {i} is contained by {[+high]} = {i, u}. Thus, every segment that is [+front] is a member of {[+high]}, in other words [+front] $\Rightarrow$ [+high]. Featural redundancy can be 'read off of' the lattice.

The representation of the phonological inventory using features and natural classes does not treat the knowledge required to classify phonological categories in a special way. Any domain where objects can be defined on the basis of distinctive properties could also be represented using the redundancy hierarchy and lattices. In general, work in cognitive psychology has focussed on constructed feature sets which are orthogonal, so that there is no redundancy. It is hoped that applying the formally coherent representation of redundancy using structured specification to create a redundancy sensitive metric of similarity in this paper will encourage work which examines the effects of redundant versus distinctive information in general cognition.

1.3 Representation of the English consonant inventory

The feature assignments I use for the English consonant segments are given in Appendix 1. All features are monovalent features. The feature assignments were made with three goals in mind. First, I attempted to represent the natural classes of English consonants. Many of the features are thus familiar ones from Chomsky & Halle 1968 and Jakobson, Fant, & Halle 1952. Second, the features are based on articulatory or acoustic properties. While articulatorily based features have been the standard, Stevens & Keyser 1989 discuss a number of acoustic correlates of many of the features used here. Third, all segments had to be individuated. The feature inventory is thus rich enough to distinctively identify every segment. The classifications presented in Ladefoged & Maddieson 1996 were used as an overall guide. Features are grouped into second order feature classes (see Frisch 1996, chapter 2, for a detailed discussion).

There is a well defined redundancy hierarchy for the English consonants. Displaying such a hierarchy graphically is impractical, however, as it is extremely large and complex.

2. Similarity

Features represent the degree of similarity between two segments. If two segments share a feature, they pattern together for any phonological phenomena that depend on that feature. Further, if features are grounded in articulatory or auditory contrast, then there is a degree of 'superficial' similarity between segments that share a feature. Psycholinguists typically use simple feature counting in quantitative arguments for similarity effects (e.g., Shattuck-Hufnagel & Klatt 1979) and have compared different feature representations by comparing their predictions for similarity (e.g., van den Broeke & Goldstein 1980, Stemberger 1991b). In this paper, I present a model of similarity originally proposed in Frisch, Broe, & Pierrehumbert 1995 that has significant empirical and conceptual advantages over feature counting models.

The model I adopt computes similarity using the natural classes of the redundancy hierarchy (Frisch, Broe, & Pierrehumbert 1995). Thus, features still play a role in determining similarity, but *relations* between features influence similarity as well. Computing similarity using the redundancy hierarchy takes into account the distinctive or redundant status of a feature. Redundant features have less influence on similarity than distinctive ones (Frisch, Broe, & Pierrehumbert 1995). In computing similarity over the redundancy hierarchy, conjunctions of features in addition to individual features contribute to the determination of similarity. Conjunctions of features have been shown to influence similarity judgments (Hayes-Roth & Hayes-Roth 1977; Gluck & Bower 1988; Goldstone, Medin, & Gentner 1991; see Goldstone 1994a). Connectionist or spreading activation models of similarity can capture the influence of conjunctions of features (Gluck & Bower 1988, Goldstone 1994a). The metric of similarity I adopt is a closed form alternative to connectionist models for computing the similarity of segments (Frisch 1996).

2.1 Similarity in the redundancy hierarchy

The similarity model I employ computes similarity based on shared and non-shared natural classes.

(5) $$\text{similarity} = \frac{\text{shared natural classes}}{\text{shared natural classes} + \text{non-shared natural classes}}$$

In the natural classes model of similarity, the self-similarity of every segment is 1, by assumption, and similarity ranges over [0,1]. In addition, similarity is symmetric in this model. We can compute sample similarity values for the three vowel inventory. Similarity values for the three vowels based on the lattice shown above are given in Table 1.

Table 1: Similarity of {a, i, u} using natural classes.

	/a/	/i/	/u/
/a/	1		
/i/	1/5	1	
/u/	2/5	2/5	1

2.2 The problem of features and redundancy

It has been argued that the cognitive notion of similarity is only well defined if the computation of similarity can be based in a principled manner on a reasonable and relevant set of features (Goodman 1972; Tversky 1977; Medin, Goldstone, & Gentner 1993; see Goldstone 1994b for a review). If the computation is only based on counting individual features, the type and number of features used has a great deal of influence on the computation.

The system of natural classes is only altered by adding features which create new natural classes; in other words, features which are contrastive within the set of segments. The set of relevant features is thus based on attributes across the entire inventory and not just for one individual segment. There are, at most, 2^n natural classes that can be created out of a set of n objects, so there is a strict upper bound on the number of features that can affect similarity in the system. In phonological classification, as the number of features increases, the level of redundancy in the feature matrix also increases.

Tversky 1977 demonstrates experimentally that 'diagnostic factors' influence the effect a particular feature has on similarity. He writes (342):

> The diagnostic factors are highly sensitive to the particular object set under study. For example, the feature "real" has no diagnostic value in the set of actual animals, since it is shared by all actual animals and hence cannot be used to classify them. This feature, however, acquires considerable diagnostic value if the object set is extended to include legendary animals, such as a centaur, a mermaid, or a phoenix.

Tversky's diagnostic and non-diagnostic features are equivalent to the distinctive and redundant features in linguistic theory. Computing similarity over the redundancy hierarchy gives differential weight to features based on redundancy, providing a model of Tversky's diagnostic factors. Contrastive features have more influence than redundant ones because of their role in defining distinctive natural classes.

By computing similarity over the natural class structure, three degrees of redundancy are differentiated. The first case is a TOTALLY REDUNDANT feature. A totally redundant feature adds no new natural classes to the redundancy hierarchy. The feature [+round] in the three vowel inventory has this property. The addition of a totally redundant features does not affect similarity. Totally redundant features are not independently contrastive. A feature can also be PARTIALLY REDUNDANT. A classic example of partial redundancy is found in the voicing of sonorants. The feature [+voice] is redundant for sonorants, but [+voice] is contrastive for obstruents. Similarly [+obstruent] is redundant for voiceless consonants, but contrastive among voiced ones. Partially redundant features have a reduced effect on similarity. Since [+voiceless] consonants are always obstruents, the set {[+obstruent]} $\supset$ {[+voiceless]}. When determining similarity between voiceless obstruents, they will have a shared natural class due to the [+voiceless] feature, and a shared natural class due to the [+obstruent] feature. By contrast, when determining similarity between voiced obstruents, they will have a shared natural class for [+voice] and a shared natural class for [+obstruent], as well as a shared natural class for [+voice]&[+obstruent]. Thus, all other things being equal, the voiceless obstruents are less similar to one another than the voiced obstruents. Features like [+voice] and [+obstruent] in the previous example, or [+high] and [+back] in the three vowel inventory, are NON-REDUNDANT with respect to one another. Note that redundancy can only be determined with respect to a particular segment inventory and feature matrix. The form of the redundancy hierarchy, and consequently the similarity values, change on a context dependent basis. Some languages employ voiceless sonorants, and in those languages, [+sonorant] is a non-redundant feature. Non-redundant features have the greatest effect on similarity, as they contribute natural classes based on their individual features, as well as conjunctions with other features.

2.3 Synergistic effects in similarity

We saw above that non-redundant features increase similarity in a more than linear manner. When segments share two non-redundant features, they share three natural classes. When segments share three non-redundant features, they share seven natural classes: {[+F1]}, {[+F2]}, {[+F3]}, {[+F1]&[+F2]}, {[+F1]&[+F3]}, {[+F2]&[+F3]}, {[+F1]&[+F2]&[+F3]}. When segments share n non-redundant features, they share 2^n-1 natural classes.

Synergistic effects of multiple feature matches on similarity have been found in experiments on categorical cue learning (Hayes-Roth & Hayes-Roth 1977, Gluck & Bower 1988) and in direct similarity judgments (Goldstone, Medin, & Gentner 1991). The synergy of multiple feature matches has been modeled using a SIMPLE AND CONJUNCTIVE FEATURES MODEL (see Goldstone 1994a). This model counts features and conjunctions of features toward similarity. This is identical to the natural classes model in the case of non-redundant features. The natural classes model has an advantage over the simple and conjunctive features model when redundancy is encountered among the features. This synergistic property has also been modeled using network of spreading activation models of similarity (Gluck & Bower 1988, Goldstone 1994a). The lattice representation provides a close match to the implementation of similarity by spreading activation. An explicit comparison of the natural classes similarity model and a spreading activation model can be found in Frisch (1996, chapter 3).

2.4 Similarity of English consonants

Using the redundancy hierarchy derived from the feature specifications given above (which was not displayed as a lattice due to its size and complexity) and the natural classes similarity model, I computed the similarity of all English consonant pairs. Appendix 2 presents the pairwise similarity of the consonants of English that I will be using in the analysis of speech errors below. I believe that roughly comparable similarity values would result from different feature assignments in the natural classes model, but I will show that these feature assignments make a good prediction of speech error rates.

3. English speech errors and similarity

I compare the natural class similarity model with a number of feature-based similarity models, using different assumptions about the nature of phonological representations, and show that the natural classes model provides a better prediction of error rate than any other model.

3.1 Data and Measure

A speech error is a spontaneous unintentional deviation from the intended utterance. Phonological speech errors are errors which are based on phonological shape. Examples of phonological speech errors are given in (6), the error is presented along with the intended target in parentheses (errors taken from Fromkin 1971).

(6) a. correcting (collecting)
 b. a hunk of jeep (a heap of junk)
 c. plan the seats (plant the seeds)

In this paper, I examine a corpus of single segment errors between two consonants published in Stemberger 1991a. The example in (6a) is such an error. Each single segment error has a TARGET, the intended phoneme, and an INTRUSION, the erroneous phoneme which is actually produced. For example, in (6a) the target is /l/, and the intrusion is /r/. Stemberger 1991a presents a confusion matrix of single segment consonant errors caused by the interaction of one segment in the utterance plan with another. Examples in (7) are from Stemberger 1991a. Interactions can involve the ANTICIPATION of one segment for another (7a), the PERSEVERATION of a previously uttered segment (7b), or an EXCHANGE of positions by two segments (7c).

(7) a. setting ... getting such bad luck
 b. about six seat (about six feet)
 c. like box (bike locks)

The errors in (7) provide evidence that sentence production involves some degree of advance planning in phonological production. For an anticipation error to occur, the intruding segment must be accessible at the time of the error, even though that particular segment is not due to be immediately produced. See Levelt 1989 for a review of error evidence in a model of language production.

Appendix 3 shows the distribution of a total of 1273 single-segment interaction errors published in Stemberger 1991a. The target segment is indicated in the left column. The intrusion segment is given across the top row. Informal inspection indicates that many errors occur between similar segments, and few occur between dissimilar segments. However, the absolute number of errors is deceiving, as some segments are much more frequent in speech, and in speech errors, than others. A measure of error rate which factors out base rate of occurrence is needed.

Following Pierrehumbert 1993, I use a measure of error rate which compares the number of errors which are observed to the number that would be expected if consonants were to substitute for one another at random. Random chance is determined by assuming using the actual frequencies of segments as targets and intrusions in the error corpus being studied. For example, /p/ is a target in 84 errors, so the probability of /p/ as a target is 0.066 = 84/1273. Similarly, /f/ is an intrusion in 69 errors, so the probability of /f/ as an intrusion is 0.054 = 69/1273. The relative probability of a /p/-/f/ error is thus $p(\text{p,f}) = 0.00358 = 0.066 \times 0.054$. The expected number of errors for each pair is:

$$\text{(8)}\quad \text{Expected}(x,y) = \frac{p(x,y)}{\Sigma_{i \neq j} p(x_i, y_j)} \bullet \text{Total errors}$$

Note that the extra factor $\Sigma_{i \neq j} p(x_i, y_j)$ is included because some of the expected frequency based solely on chance includes expected errors between identical consonants. Errors between identical segments, if they do occur, cannot be detected, so a certain amount of the marginal probability is lost from the total. The extra factor is used as an adjustment to distribute errors by expected frequency over all non-identical pairs. In other words, expected counts of consonants interacting with themselves are assumed to be zero and the other expected values are increased to insure that the total number of errors is correct.

The ratio of the number of observed errors to the number of expected errors (O/E) provides a measure of error rate which factors out the frequencies of targets and intrusions. The measure of O/E is a measure of the error rate between consonants independent of their frequency.

$$\text{(9)}\quad \text{O/E} = \frac{\text{Observed(x,y)}}{\text{Expected(x,y)}}$$

3.2 Natural class similarity and interaction errors

Table 2 presents aggregated total numbers of actual errors and expected errors for different levels of similarity in Stemberger's corpus of interaction errors:

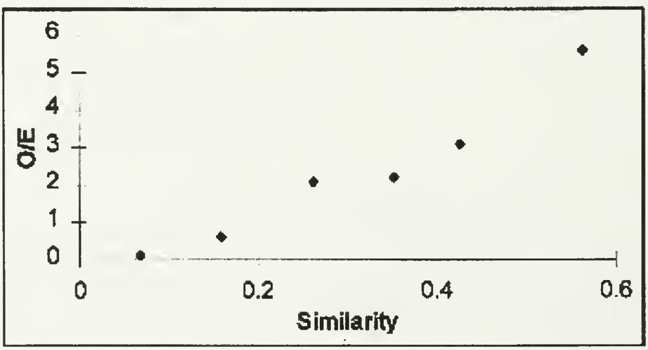
Table 2: Interaction errors aggregated by natural class similarity.

Similarity	Example pairs	Observe	Expected	O/E
0-0.1	(f,d), (θ,m), (p,y), (k,r)	72	519.3	0.14
0.1-0.2	(m,d), (b,t), (f,k), (g,r)	246	416.5	0.59
0.2-0.3	(b,d), (ð,d), (s,h), (m,n)	234	113.5	2.06
0.3-0.4	(f,v), (t,d), (t,k), (n,N)	195	88.2	2.21
0.4-0.5	(f,θ), (ð,z), (d,dʒ), (w,r)	288	93.1	3.09
0.5-0.6	(s,ʃ), (z,ʒ), (r,l), (n,l)	238	42.4	5.61

Four consonant pairs for each similarity class are given as examples.The right-most column of Table 2 is the O/E measure of error rate based on the aggregate observed and expected totals.

Figure 2 plots aggregate O/E against similarity. While the data have been aggregated, the groupings used in the aggregated similarity measure are still more sensitive than similarity measures previously used in speech error analyses. Most error analyses use three basic feature categories: place, manner, and voicing. Similarity is computed by counting the number of these basic features that are the same between two consonants (e.g., Nooteboom 1969, MacKay 1970, Shattuck-Hufnagel & Klatt 1979, van den Broeke & Goldstein 1980, Levitt & Healy 1985). For example, /p/ and /t/ share two features, manner and voicing, but differ by place. In this measure, there are only four relevant levels of similarity (0, 1, 2, or 3 shared features). The aggregated similarity in Table 2 differentiates six levels of similarity. The fact that error rate increases monotonically justifies the more precise measure of natural class similarity.

Figure 2: Interaction errors aggregated by natural class similarity.



The natural classes similarity metric provides a good prediction of error rate in Stemberger's corpus. However, the natural class model involves additional assumptions about the representation of segments, the effect of redundant features on similarity, and the synergistic effects of multiple feature matches. The natural classes model can be compared to a number of other models of similarity that are based only on features.

3.3 Similarity model of Stemberger 1991b

Stemberger 1991b considers the effect which the assumption of radical underspecification might have on similarity and hence on speech error rates. He hypothesizes that, if speech errors can occur at a point in the phonological derivation where segments are still underspecified for some features, then underspecified features should have no effect on the similarity of consonants at that time. Thus, underspecified features should play no role in determining error rates early in the derivation. If speech errors can occur at more than one point in the derivation, underspecified features may only be relevant for some error opportunities and thus have a reduced effect on error rate.

Consider, for example, the difference between the following fully specified and radically underspecified representations of {p, f, t, s}.

(10) Fully specified feature matrix / Radically underspecified feature matrix

	p	f	t	s		p	f	t	s
sonorant	-	-	-	-	sonorant				
continuant	-	+	-	+	continuant		+		+
voice	-	-	-	-	voice				
Labial	%	%			Labial	%	%		
Coronal			%	%	Coronal				
anterior			+	+	anterior				

In the radically underspecified feature matrix, [Labial] is specified, but [Coronal] is left blank and filled in by a default rule in the course of the phonological derivation. Thus, Stemberger observes, in the radically underspecified representation, /p/ and /f/ share a feature for which the corresponding pair /t/ and /s/ are underspecified. Since shared features increase similarity (Tversky 1977), the radically underspecified feature matrix predicts that /p/ and /f/ should be more similar to one another than /t/ and /s/. Thus, /p/ and /f/ should have higher error rates with one another than /t/ and /s/.

In support of his claims, Stemberger 1991b considers quantitative evidence from his corpus of naturally occurring speech errors which I will not review in detail here (see Stemberger 1991b, Frisch 1996). Stemberger takes these differences in error rate as support for underspecified underlying representations. Stemberger 1991b proposes a two stage model of speech errors in which errors can occur either before or after underspecified features are filled in. In this model, the similarity of consonants at each stage is different because at the early stage consonants are underspecified and at the later stage they are fully specified. Error rates in the early stage are only influenced by specified features, while errors rates at the second stage are influenced by all features. However, Stemberger 1991b does not provide an explicit similarity metric (Thompson 1995) or test his assumptions about underspecification and similarity over any other sets of consonants.

As mentioned above, Stemberger 1991b only considers minimal contrasts involving underspecification and does not consider the effect that underspecification has on similarity, and therefore error rate, across the entire inventory. Stemberger does not present an explicit similarity metric, and opts instead to point out in general how the contrasts he examines could be predicted by similarity and underspecification on a case by case basis.

Stemberger makes the following assumptions about similarity (Thompson 1995):

(11) 1. Shared specified, but not underspecified, features increase similarity.
2. Different specified, but not underspecified, features decrease similarity.[2]
3. For two consonants where one feature is specified and one under specified, similarity is less than between two consonants which are both underspecified.

The similarity model which is closest to the natural classes model that satisfies these assumptions is the metric of similarity in Pierrehumbert 1993, given in (12). I take this to be the implicit model behind Stemberger's discussion, since this model satisfies all of the assumptions in (11).

$$\text{(12) similarity} = \frac{\text{shared features}}{\text{shared features + non-shared features}}$$

Stemberger's feature assignments are based on a survey of contemporary literature involving underspecification as well as feature geometry. I simply adopt his feature assignment as representative of the effect that the assumption of underspecification has on similarity and feature assignment in linguistic theory. Similarity was computed using Pierrehumbert's metric for radically underspecified, contrastively underspecified, and fully specified feature matrices. Due to space limitations, details are not presented here (see Frisch 1996, chapter 8).

Stemberger 1991b claims that specified features have the greatest effect on similarity, and that underspecified features have a smaller influence. Stemberger's model thus involves errors at two stages, before and after specification. Other plausible models of similarity involve a single stage using specified features under either radical underspecification or contrastive underspecification, and a model based only on the fully specified similarity computed with analogous features. All of these models can be compared to the natural classes similarity model.

3.4 Simple models

There are three simpler models of speech errors which we might prefer to use for parsimony. The first I call the FREQUENCY MODEL, which assumes that similarity is not a factor in errors, and the predicted number of errors is equal to the number expected as computed above. Since similarity is a well known factor in speech errors, this model has a poor fit but it is included as a baseline to show how much of the error rate is accounted for solely by base rate of occurrence. The second model is the SIMPLE FEATURE MODEL. In this model, similarity is based on simple place, manner, and voicing contrasts, as mentioned in section 3.2. This model has only four distinct similarity values. The third model is the COMPLEX FEATURE MODEL. This model is based on the same features used in the computation of similarity over natural classes, given in Appendix 1, but instead similarity is computed based on shared and non-shared features (equation 12).

4. Model comparison and results

All models are compared by fitting them to Stemberger's 1991a consonant confusion matrix. Each model is fit with a non-linear regression to predict the actual number of errors for each pair, with the expected number of errors and similarity as predictor variables. The regression equation is:

(13) Observed = Expected x (A + B x Similarity)

In the case of Stemberger's two stage model, the equation is:

(14) Observed = Expected x (A + B x Underspecified Sim + C x Specified Sim)

These equations are roughly equivalent to linear regression on O/E, however using non-linear regression gives the greatest weight to consonant pairs that have either a large number of actual errors or have a large number of expected errors. O/E is unstable for small values, which makes it unsuitable for use in regression. The regression was performed on unaggregated data. The models attempt to predict the actual error rate for each consonant pair as target and intrusion. Table 3 shows model fits and parameters for the frequency model and all similarity models.

Table 3: Eight models of Stemberger's corpus of consonant speech errors.

Model	R^2	Parameters
Frequency Model	0.17	none
Radical Underspecification	0.35	A (constant) = 0.65, B (similarity) = 5.4
Contrastive Underspecification	0.44	A = -0.19, B = 5.1
Full Specification	0.49	A = 0.65, B = 5.8
Simple Feature Model	0.57	A = -0.61, B = 1.37
Complex Feature Model	0.57	A = -0.56, B = 6.06
Two-stage model	0.57	A = -0.57, B (underspec) = 3.8, C (spec) = 4.9
Natural classes model	0.72	A = -0.69, B = 9.88

The frequency model has very poor fit, similarity is clearly a factor in error rate. Among the models based on standard linguistic feature matrices, the fully specified model has the best fit, followed by the contrastive underspecification model, and then the radical underspecification model. Of course, the two stage model provides a better fit than either the radical underspecification model or the specified feature model, since it is equivalent to either of these models with an additional parameter. The simple feature model fares as well as the two-stage model, suggesting that there is nothing to be gained by assuming complex underspecified representations and a derivational procedure that fills in redundant features. Surprisingly, the complex feature model also does no better than the simple feature model. This suggests that 'primary features' (Stevens & Keyser 1989) might be the only relevant features for determining similarity. However, the natural classes similarity model is far superior to the simple feature model, and all other models. Thus it is not that the additional (secondary) features are not relevant, or that redundant and/or default features are underspecified, but that feature similarity does not properly differentiate features by contrastiveness and redundancy the way the natural classes model does. The additional assumptions of the natural classes model, where redundancy can be found to various degrees and therefore has gradient effects on similarity, are supported by the data.

NOTES

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[1] In this paper, I use all monovalent features The use of two monovalent features, [high] and [low] is notationally equivalent to using a single bivalent feature [±high]. See Frisch (1996, chapter 2) for a detailed discussion of the issues.

[2] Note that this situation does not arise for monovalent features It can only occur with bivalent or multivalent features.

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APPENDIX 1.

ARTICULATOR features:

	p	b	f	v	m	t	d	θ	ð	s	z	ʃ	ʒ	tʃ	dʒ	k	g	ŋ	l	r	n	w	y	h
labial	+	+	+	+	+															+		+		
coronal						+	+	+	+	+	+	+	+	+	+			+	+	+		+		
dorsal																+	+	+						

PLACE features:

	p	b	f	v	m	t	d	θ	ð	s	z	ʃ	ʒ	tʃ	dʒ	k	g	ŋ	l	r	n	w	y	h
bilabial	+	+			+															+		+		
dental			+	+				+	+															
alveolar						+	+			+	+							+	+	+				
palatal												+	+	+	+								+	
velar																+	+	+						

STRICTURE features:

	p	b	f	v	m	t	d	θ	ð	s	z	ʃ	ʒ	tʃ	dʒ	k	g	ŋ	l	r	n	w	y	h
obstruent	+	+	+	+		+	+	+	+	+	+	+	+	+	+	+	+	+						+
sonorant					+													+	+	+	+	+	+	
stop	+	+			+	+	+							+	+	+	+	+						
continuant			+	+				+	+	+	+	+	+											+
glide																						+	+	
consonantal					+														+	+	+	+		

MANNER features:

	p	b	f	v	m	t	d	θ	ð	s	z	ʃ	ʒ	tʃ	dʒ	k	g	ŋ	l	r	n	w	y	h
oral	+	+				+	+									+	+							
affricate														+	+									
strident										+	+	+	+	+	+									
distributed			+	+			+	+															+	
lateral																			+					
rhotic																				+				
nasal					+													+			+			

LARYNGEAL features:

	p	b	f	v	m	t	d	θ	ð	s	z	ʃ	ʒ	tʃ	dʒ	k	g	ŋ	l	r	n	w	y	h
voice		+		+	+		+		+		+		+	+		+	+	+	+	+	+	+		
voiceless	+		+		+		+		+	+		+			+								+	
spread glottis																								+

Appendix 2.

Similarity of English consonant pairs using the natural classes model.

	p	b	f	v	m	t	d	θ	ð	s	z	ʃ	ʒ	tʃ	dʒ	k	g	ŋ	l	r	n	w	y	h
p	1																							
b	0.4	1																						
f	0.26	0.13	1																					
v	0.15	0.3	0.38	1																				
m	0.19	0.39	0.07	0.15	1																			
t	0.3	0.14	0.1	0.06	0.06	1																		
d	0.14	0.28	0.05	0.11	0.11	0.39	1																	
θ	0.11	0.06	0.43	0.19	0.03	0.2	0.11	1																
ð	0.07	0.12	0.19	0.39	0.06	0.12	0.23	0.38	1															
s	0.1	0.05	0.18	0.1	0.03	0.3	0.15	0.4	0.2	1														
z	0.06	0.11	0.09	0.19	0.6	0.17	0.33	0.19	0.44	0.37	1													
ʃ	0.1	0.05	0.18	0.1	0.03	0.18	0.1	0.4	0.2	0.58	0.24	1												
ʒ	0.06	0.11	0.09	0.19	0.06	0.11	0.2	0.19	0.44	0.24	0.57	0.37	1											
tʃ	0.21	0.11	0.1	0.06	0.06	0.44	0.22	0.21	0.13	0.27	0.14	0.41	0.21	1										
dʒ	0.11	0.22	0.06	0.11	0.11	0.22	0.47	0.11	0.24	0.13	0.28	0.19	0.44	0.39	1									
k	0.44	0.19	0.14	0.08	0.08	0.35	0.16	0.13	0.08	0.11	0.06	0.11	0.06	0.25	0.13	1								
g	0.21	0.42	0.08	0.16	0.15	0.17	0.33	0.07	0.15	0.06	0.13	0.06	0.13	0.14	0.27	0.39	1							
ŋ	0.09	0.15	0.04	0.09	0.37	0.07	0.13	0.04	0.08	0.04	0.07	0.04	0.07	0.07	0.13	0.17	0.33	1						
l	0.04	0.07	0.04	0.08	0.17	0.11	0.19	0.08	0.17	0.11	0.22	0.07	0.14	0.07	0.13	0.05	0.09	0.24	1					
r	0.1	0.19	0.07	0.14	0.44	0.09	0.16	0.06	0.13	0.09	0.18	0.06	0.11	0.06	0.11	0.04	0.07	0.17	0.56	1				
n	0.06	0.12	0.03	0.06	0.26	0.19	0.38	0.06	0.13	0.09	018	0.06	0.11	0.12	0.24	0.07	0.14	0.33	0.53	0.4	1			
w	0.14	0.25	0.09	0.19	0.44	0.03	0.06	0.04	0.08	0.04	0.07	0.04	0.07	0.04	0.06	0.05	0.09	0.18	0.17	0.42	0.12	1		
y	0.04	0.07	0.04	0.09	0.13	0.07	0.13	0.08	0.17	0.07	0.14	0.12	0.23	0.12	0.21	0.05	0.09	0.18	0.40	0.29	0.27	0.25	1	
h	0.15	0.08	0.47	0.21	0.04	0.12	0.06	0.41	0.19	0.23	0.11	0.23	0.11	0.13	0.07	0.19	0.1	0.06	0.06	0.04	0.04	0.06	0.06	1

Appendix 3:
Confusion matrix of interaction errors from Stemberger 1991b

	p	b	f	v	m	t	d	θ	ð	s	z	ʃ	ʒ	tʃ	dʒ	k	g	ŋ	l	r	n	w	y	h	Total
p		5	25	0	4	22	0	1	0	3	0	0	0	0	0	21	0	0	0	0	0	0	0	3	84
b	9		3	4	7	2	11	0	0	1	0	0	0	0	1	1	10	0	5	2	1	6	0	1	64
f	8	1		1	1	3	0	5	0	22	0	1	0	3	0	4	0	0	0	0	1	1	0	9	60
v	3	6	2		2	2	1	0	1	0	2	0	0	0	1	0	3	0	2	1	0	0	0	0	26
m	4	7	0	4		0	1	0	0	0	1	0	0	0	0	2	0	1	3	3	19	8	0	3	56
t	22	2	1	0	0		6	7	1	13	3	2	0	15	1	42	0	0	3	1	6	0	0	8	133
d	0	5	2	1	0	11		0	0	3	5	2	0	0	6	0	20	0	5	2	9	1	1	1	74
θ	0	1	3	0	0	2	0		0	16	0	2	0	1	0	0	0	0	0	1	0	0	0	2	28
ð	0	0	0	1	0	0	4	0		1	0	0	0	0	1	0	0	0	2	1	0	1	0	1	12
s	3	0	16	0	1	11	1	29	0		0	58	0	6	0	1	0	0	0	0	0	0	0	7	133
z	1	0	0	6	0	3	1	0	1	1		0	1	0-	1	0	0	0	1	1	1	0	0	0	18
ʃ	0	0	1	0	0	2	0	1	1	33	0		0	1	0	1	0	0	0	0	0	1	0	0	41
ʒ	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	0	0	0	0	0	0	0
tʃ	1	1	0	0	0	9	0	0	0	7	1	1	0		1	4	0	0	0	0	0	0	0	1	26
dʒ	1	1	1	0	0	1	9	0	0	3	1	0	0	0		0	0	0	0	1	0	0	0	0	18
k	21	1	7	1	0	28	1	2	0	11	0	0	0	9	0		8	1	1	1	0	0	0	5	97
g	0	8	1	0	0	1	2	0	0	1	2	0	0	0	2	5		1	1	0	0	0	0	0	24
ŋ	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	3	0	0	0	3
l	0	1	1	1	3	3	2	0	0	0	0	0	0	0	0	2	0	0		55	8	11	12	2	101
r	0	1	0	0	3	0	4	0	0	0	0	0	0	0	0	0	0	0	67		1	20	2	0	98
n	0	1	0	0	23	5	7	0	0	1	1	0	0	0	1	5	0	1	16	4		0	0	4	69
w	1	5	1	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	9	27	1		4	1	60
y	0	0	0	0	1	0	0	0	0	0	0	2	0	1	0	0	0	0	11	2	0	1		0	18
h	0	0	5	1	0	2	1	1	0	6	0	1	0	1	0	10	1	0	0	0	1	0	0		30
Total	74	46	69	20	55	107	51	46	4	122	16	69	1	37	15	98	43	4	126	102	51	50	19	48	1273