Phonetic Ambiguity: Approaches, Touchstones, Pitfalls, and New Directions

Patrick Juola
Department of Experimental Psychology
Oxford University
South Parks Road
Oxford, UK OX1 3UD
patrick.juola@psy.ox.ac.uk

Abstract

Phonetic ambiguity and confusibility are bugbears for any form of bottom-up or data-driven approach to language processing. The question of when an input is “close enough” to a target word pervades the entire problem spaces of speech recognition, synthesis, language acquisition, speech compression, and language representation, but the variety of representations that have been applied are demonstrably inadequate to at least some aspects of the problem. This paper reviews this inadequacy by examining several touchstone models in phonetic ambiguity and relating them to the problems they were designed to solve. An good solution would be, among other things, efficient, accurate, precise, and universally applicable to representation of words, ideally usable as a “phonetic distance” metric for direct measurement of the “distance” between word or utterance pairs. None of the proposed models can provide a complete solution to the problem; in general, there is no algorithmic theory of phonetic distance. It is unclear whether this is a weakness of our representational technology or a more fundamental difficulty with the problem statement. In any case, these results show that the representations can be as crucial as the system architecture, and that as much or more creativity is required to properly represent language as to process it.
1 Motivations

When is a sound one word and not another? This is, in many regards, the fundamental question for spoken language processing. At a minimum, any system must be capable of converting the infinite variety of human speech into a distinct set of words, regardless of the subsequent processing to be performed. Somehow, a system must distill the relevant and important information from the highly noisy and ambiguous sound signals. And, although systems will differ slightly on what are considered to be “relevant,” certain characteristics appear to be universal, regardless of the system/model—and thus it makes sense to talk about an “ideal” representation, suited to any purpose.

What properties would an ideal sound and language representation scheme have? As a first pass it should be capable of accurately representing the important contrasts. It would be broadly useful to the exact extent that it can represent a wide and hopefully universal range of words. An ideal representation should be useful for as wide a range of problems as possible, including the modeling of human language processing. And for many applications, it should be reversible so that representations can be reconverted in words at the end of some form of processing.

Efficiency of storage and manipulation is another desideratum, as language applications often require that thousands of words and millions of sentences be stored and analyzed. It would be useful if the representation could be related to psycholinguistic perception and/or production theories. Similarly, the more accurately the representation can capture cognitive facts, the fewer representational artifacts it will introduce into (e.g.) modeling work. Another important characteristic of an ideal system is what it does not represent. For most applications aspects of speech such as sex, health, and accent of the speaker should be ignored, or in other words, the representation should be speaker-independent. For engineering reasons, the representation should be modular and reusable, so that the same wheel need not be continually reinvented. Finally, it should also be symbolically decomposable, so that, a researcher can knowledgeably manipulate the effects of specific phenomena such as stress, prosody, or accent.

A rather more controversial claim is that the representation should include a meaningful distance measurement. For most applications, it would be convenient if one sound pattern could be said to be “closer” to a desired word than another — e.g. providing guidance in a language learning experiment. A distance metric could aid case-based reasoning and/or error recovery by providing a measure of confidence, confusibility, or likelihood. However, to conjecture that phonetics can be approximated by a metric space is a very strong mathematical statement; although such would be desirable, much further work would be required to firmly establish that claim. However, this property is important enough for engineering reasons that it seem reasonable
to include this as a significant factor in evaluating representation systems.

2 Sound signals

The simplest and easiest way of representing sound is to use the acoustic signal itself. No technique can be more faithful of reproduction or easily reversible. Cognitive plausibility is immediate and obvious, and application is clearly universal. Applications in speech processing that use the speech signal itself without a separate unit performing preprocessing are too many, common, and varied to require individual mention; any recent COLING, ICSLP, or ACL proceedings will list several applications.

Unfortunately, this is one of the least efficient representations available, in terms of both storage and processing. It is also legendary for being speaker-dependent, enough so to be used as the key to several security systems (e.g. PGPfone[8]). A more serious objection to its use is that the usual purpose for language representations is to simplify the task of processing by eliminating extraneous, useless, or noisy information. Any two applications are likely to jointly consider at least some of the information, such as speaker-dependence, to be extraneous, and thus the sound signal itself is best treated as a base case, or as a reserve representation when no other one presents itself.

3 Russell/SOUNDEX

One of the earliest attempts to model phonetic ambiguity derives from the representation of names. For example, an important letter addressed to the “Brown” family may actually be intended for the Braun family. The Russell/SOUNDEX encoding (described in [7]) provides a method of encoding names to reduce or eliminate misclassification errors caused by similar sounding names or transcription errors.

SOUNDEX represents words (usually names) as four character strings. The first character of the name becomes the first character of the code string. Every subsequent character in the name is looked up according to the scheme presented as Figure 1 and encoded as one of the digits 1-6. The first three (coded) characters are appended to the initial letter and are used as the word coding—if there are insufficient characters remaining in the name, the coding is padded with zeros. Two adjacent identically coded letters (for example, the double ll in “Miller”) are treated as a single letter.

For example, the name “Juola” would be coded as J400. The initial J is transcribed unchanged, the U and the O are ignored, the L is coded as a 4, the A is ignored, and the code is padded with zeros to a full four characters. Similarly, “Krumplestater” and “Kruempelstaedter” would both be coded as K651.
1 = B,P,F,V  4 = L  
2 = C,S,G,J,K,Q,X,Z  5 = M,N  
3 = D,T  6 = R  

All other letters (A,E,I,O,U,Y,W,H) ignored  

Figure 1: Russell/SOUNDEX coding guide  

Within the limited domain of filing names, SOUNDEX works extremely well. SOUNDEX coding is simple to perform by hand, efficient to implement on a computer, and robust to most transcription and misspelling errors. Furthermore, it is robust to most accent or pronunciation variations, meaning that it will integrate well into a text-based system with voice input, such as an (automated) airline reservation system. Names of arbitrary length are conveniently compressed to a uniform size and format.

However, the number of false positives, names that are incorrectly grouped together, is much higher. For example, B560 codes the “Bonner” variants as well as “Baymore.” V525 is “Van Hoesen” as well as “Vincenzo.” There being fewer than 9000 classes in total, a large number of false-positive errors is almost certain to arise. Furthermore, names in certain categories can cause an unacceptable amount of clustering, and it has proved necessary for some applications to significantly modify the SOUNDEX coding (e.g. the Daitch-Motokoff variant for Jewish names). The application of the SOUNDEX scheme is thus highly use specific and marginally language specific as well.

The greatest problem with the universal application of a SOUNDEX-like encoding to language problems is the absence of a distance measure. As with a hash table, there’s no sense in which numbers/names in one category can be meaningfully stated to be close or distant from another category – or even in which categories can meaningfully be considered to be equivalence classes. The coding scheme is non-invertible; there is no way to reconstruct a name from its SOUNDEX category. Finally, although the system is relatively robust to spelling variations, there are certain categories of errors to which it is extremely sensitive. For example, changing the initial consonant of a name (“Cramer” to “Kramer”) or insertion or deletion of a letter (“Boughman” to “Bowman”) can change the coding of the name, and there’s no practical method of identifying a set of “neighboring categories” into which a (mis)coding might fall.

4 Templates and PGPfone

Another simple method of performing word to word comparisons is to simply divide word (pairs) into elements and perform comparisons on those elements.

\[\text{[see } \text{http://http://www.genealogysf.com/glenda.htm]}\]
| Feature name        | Sample         | Weighting |
|---------------------|----------------|-----------|
| Place of articulation | /d/ vs /g/   | 7         |
| Manner of articulation | /l/ vs /t/   | 6         |
| Height of articulation     | /i/ vs /ɛ/   | 5         |
| Voicing               | /z/ vs /s/   | 4         |
| Syllabic             | vowels vs. cons. | 1        |
| Nasal                | /n/ vs /d/   | 1         |
| Lateral              | /l/ vs /ɹ/   | 1         |
| Roundedness          | (various)    | 1         |
| Sibilant             | /s/ vs /ɬ/   | not used  |

Figure 2: Phoneme coding for PGPfone alphabet

Phonetic theory (e.g. [5]) provides support for the notion of analyzing words as a temporal sequence of phonemes which can be individually compared. For instance the first elements (phonemes) can be compared, then the second, &c., and a total distance calculated as a function of the element distances.

This technique has been in common use in, e.g., neural net research for a number of years. A detailed example of this technique in use can be found in the PGPfone alphabet [4, 5]. This alphabet is the result of a computer search for “phonetically distinct” words using an elaborate feature-based metric. Phonetic features, as described in [4], are compared and the results of the comparison are weighted in approximate accord with psycholinguistic results on perceptual salience, as typified by [6]. Figure 2 describes this weighting in detail. Suprasegmental features such as stress pattern and the additional salience of the onset consonants are incorporated by a second level of reweighting. The various weightings can, in theory, be arbitrarily refined to match available psycholinguistic data.

Because the PGPfone metric was specifically designed as a distance metric, it can be used directly to measure closeness of fit or accuracy of a word coding. It is efficient to code and decode words, and the accuracy is as good as the psycholinguistic data it incorporates. Similarly, it merges easily with existing fields of study. It is as language, dialect, and speaker-independent as the underlying phonological representation.

In some regards, this very accuracy can be a weakness, as it can put more stress on the psycholinguistic data than the data can support. For example, [4] and similar feature sets usually describe phonemes in terms of productive differences; subtle differences such as tongue placement and place of articulation are described with much more accuracy and detail than binary features such as voicing. However, studies such as [6] indicate that, for example, voicing is usually more salient than place of articulation, and thus the word “but” is more likely to be misheard as “gut” than as “putt” under nearly all noise conditions. However, data have only been gathered
and collated for a fraction of the relevant comparison conditions; in the case of [6], for instance, only consonant comparisons were done.

A more serious weakness of the PGPfone scheme lies in the limited domain of comparison. Comparison on a phoneme by phoneme basis requires that individual phonemes to compare be aligned meaningfully. For words with an identical number of phonemes in a sufficiently similar pattern, this is nonproblematic. However, in the general case, there’s no easy and efficient algorithmic method to compare one consonant against a cluster, or a two syllable word against a five syllable one. Which, for instance, should be measured as closer to the word ”bet”, the word ”bets,” ”best”, or ”Bess”? PGPfone, like most other applications of this technique, avoids this problem by carefully restricting the domain of comparisons (for example, only words with an identical number of syllables can be meaningfully compared). This restriction can, in the domain of PGPfone, be turned into an advantage by carefully phrasing the restrictions to limit its use to words advantageous for other purposes, but in the general case, this limitation can only be overcome by lots of additional computation to determine the appropriate alignment, resulting in computational inefficiency. Again one can observe that this line of approach has serious flaws in the way of developing an ideal universal phonetic representation system.

5 Autosegmental representations

The assumption of the previous section, that words are a linear sequence of elements, may produce raised eyebrows for some modern phonologists. Autosegmental phonology [3] describes words in terms of multiple ‘tiers’ of different parallel phenomena, and the horizontal slicing into tiers is primary to the vertical time-slicing of the sound sequence itself. Words can thus be identified, classified, and compared at several levels. This can make the classification more robust to minor changes at lower levels (such as insertion of a single consonant).

Bird and Ellison[1] describe a method for algorithmically representing words in this fashion that can also be applied to determining interword compatibility at the various levels. They are content to restrict themselves to merely demonstrating the algorithm in use and to use it to develop and demonstrate a few phonological rules. The rules they develop are of the same sort used by several other researchers (e.g. [2]) in models of the production of past tenses. This is another classic touchstone problem for the testing of cognitive theories of language.

Again, these models merge well with existing phonological theory and can be used to represent any word in any language. The representations are accurate and algorithmic, with good modularity and speaker-independence. Unfortunately, the encodings for these representations (as finite-state automata)
yield tremendously inefficient algorithms, even for determining whether or not two representations describe the same words.

In [1], for instance, autosegmental tiers within a word are associated by describing each tier with a separate automaton, calculating “pinnings” between the tiers as state numberings, and then determining the final representation as a larger automaton that accepts all and only the intersection of the languages accepted by the various tiers. This method can clearly be generalized to the comparison of multiple words by determining appropriate pinnings between the representations of two words and determining whether the intersection of all tiers, of both words, is non-empty. However, the calculation of intersection of such automata is typically polynomial in the number of automata, even ignoring the difficulties in determining appropriate pinnings (as alluded to in the previous section). This formalism is thus difficult to efficiently implement on a large-scale, as would be necessary for case-based reasoning, &c.

6 Discussion and conclusions

All representations and codings discussed (with the exception of the null encoding) manage to produce contrastive representations in a speaker-independent fashion. This should not be particularly surprising, as any representation that could not distinguish relevant sounds simply wouldn’t work. On the other hand, it appears difficult if not impossible to simultaneously satisfy all three of the desiderata of algorithmic efficiency, generality of representation, and accuracy of representation. In particular, the SOUNDEX coding uses a very coarse and inaccurate representation, with no useful topological properties, but can be efficiently and effectively implemented on nearly any set of words in English. The PGPfone templates provide an efficient and detailed distance metric between any two words in an extremely restricted class selected for other engineering reasons. Autosegmental encoding, as developed by [1], is in theory extremely accurate and can capture any phonological variation of significance, but is algorithmically so inefficient as to have prevented it from being used in any major projects. None of the three approaches is capable of quickly determining an ambiguity or confusion measure between a pair of random English words.

From an engineering perspective, this is disappointing but perhaps unsurprising; the idea of “pick two and call me back” is a common joke. From a scientific point of view, the implications are more interesting. If the notion of an ideal phonological distance metric is well-founded and achievable, then the obvious question to be addressed is how to find it and what sort of data are necessary to gather. If, on the other hand, it is not possible to develop an ideal metric, what is the human solution? For example, if human language processing is not done speaker-independently, then how does the
speaker influence the processing and representation of sounds in the human brain? What are the psychological and linguistic implications of these representations? If there is no possible metrization of perceptual errors, then where do the different confusibilities arise? What sort of phenomena can be expressed in a psycholinguistically real fashion?

In the shorter term, these results indicate once again the importance of task and problem analysis for language problems. Many researchers are content, in the absence of a better metric, to treat the results of their neural networks or cluster analyses of phonetic templates as being representative of cognitive processes within the human brain. A better approach might be to treat the representation process itself with as much caution and creativity as the system architecture, rather than trusting in crude representational simplifications and hoping that these simplifications are nondestructive. A careful task analysis can, one hopes, demonstrate not only what aspects of ambiguity processing are relevant for an engineering solution to a language problem, but also the ways in which solutions to different touchstone problems, even apparently arbitrary ones such as PGPfone or SOUNDEX, can be fitted together as a scaffold for the larger psycholinguistic questions.

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