Infant Pathways to Language

Methods, Models, and Research Disorders

Edited by
John Colombo
Peggy McCardle
Lisa Freund

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What Statistical Learning Can and Can’t Tell Us about Language Acquisition

RICHARD N. ASLIN AND ELISSA L. NEWPORT

INTRODUCTION

In fall 1992, Jenny Saffran entered graduate school at the University of Rochester after having spent four years at Brown University working with Jim Morgan and an additional year as a research assistant with Sheila Blumstein. She already had an interest in the interaction between prosody and word segmentation (Morgan & Saffran, 1995) but sought a research topic for her first-year project. Ironically, in two independent consultations with each of us the suggestion was made to Jenny to read a chapter by Hayes and Clark (1970) in which adults were presented with sequences of noises that contained embedded subpatterns. Hayes and Clark reported that after listening to a continuous stream of noises, performance on a two-alternative forced-choice post-test was above chance for recognizing noise sequences that began and ended at subpattern breaks over noise sequences that began and ended within subpatterns. Four years later, after a number of fits and starts, two papers were published on adult (Saffran, Newport, & Aslin, 1996) and infant (Saffran, Aslin, & Newport, 1996) word segmentation from streams of synthetic speech. These two papers used the term statistical learning (SL)—from Charniak’s (1993) description of algorithms in computational linguistics—to describe the psychological process by which the transitional probabilities from one syllable to another in the continuous speech streams could enable word segmentation and its complement, what Hayes and Clark referred to as clustering.

It would appear that Saffran, Newport, & Aslin (1996) and Saffran, Aslin, & Newport (1996) struck a chord in the language acquisition literature. There have been dozens of follow-up experiments in the subsequent decade, and the term statistical learning is now used to described a subfield of research on impressive feats of rapid learning in a variety of domains within language and visual processing.
adults have access to highly detailed representations of the input distribution. For example, Howes and Solomon (1951) showed that adults’ word-recognition threshold in noise is a function of word frequency (estimated from written corpora). Levelt and Wheeldon (1994) showed that adults’ picture naming latency is a function of syllable frequency. Vitevich and Luce (1998) showed that adults’ lexical decision time is a function of phoneme frequency. And literally hundreds of psycholinguistic experiments have found the need to control stimuli for word and phoneme frequency, implicitly suggesting that subjects would be sensitive to these variables. Thus, there is clear behavioral evidence that mature users of a language have access to distributional information at the word, syllable, and phoneme level. And despite the “in principle” arguments for the implausibility of SL, there is demonstrable evidence that human learners overcome these impediments. How adults, and infants, do so will be discussed after reviewing recent findings on SL that extended the original studies by Saffran, Aslin, & Newport (1996) and Saffran, Newton, & Aslin (1996).

Statistical Learning since 1996

In our original studies of SL, we chose to study word segmentation because it is a tractable problem that must be solved by all language learners, and it is illustrative of a distributional learning mechanism that may apply more broadly (though we made no claim that it is sufficient). Saffran, Newport, Aslin, Tunick, and Barrreucco (1997) showed that overt attention was not necessary for SL in preschoolers or adults, although some general level of attention is required (Toro, Sinnett, & Soto-Faraco, 2005). Saffran, Johnson, Aslin, and Newport (1999) showed that SL operates as well over sequences of nonlinguistic tones—in which the statistical structure mimics that of speech syllables—in infants and adults. Perhaps most importantly, Aslin, Saffran, and Newport (1998) investigated precisely what type of statistical is used in SL on speech streams. They showed that 8-month-olds could solve the word-segmentation problem even in the absence of trisyllable co-occurrence frequency differences. When the frequency of occurrence was equated for the words and part-words that were tested after exposure to speech streams, infants still discriminated words from part-words based on the higher-order statistic of transitional probability. This does not mean that frequency is irrelevant to SL but rather that first-order frequency statistics are not the only class of statistics that infants can compute.

Fiser and Aslin (2002a) extended these results from the auditory domain to the visual domain by showing that simple visual shapes presented in temporal sequences (albeit at a slower rate than speech) enable adults to extract both first-order (frequency-based) and second-order (conditionalized) statistics. Kirkham, Slemmer, and Johnson (2002) showed that 2-, 5-, and 8-month-olds are sensitive to first-order statistics in streams of simple shapes. Hunt and Aslin (2001) showed that SL applies to the visual-motor domain in a serial reaction time task with adults. Finally, Fiser and Aslin (2001, 2002b, 2005) moved the SL literature from the temporal to the spatial domain by showing that very similar mechanisms operate in multielement visual scenes, where both adults and 9-month-olds can bind together elements on the basis of first- or second-order statistics to form coherent perceptual “chunks.”

Demonstrations of SL in nonhumans, both tamarin monkeys (Hauser, Newport, & Aslin, 2001; Newport, Hauser, Spaepen, & Aslin, 2004) and rats (Toro & Trobélón, 2005) clearly show that at least the simple aspects of SL are not unique to humans. However, only one study of nonhumans has employed the frequency-balanced design of Aslin et al. (1998), which evaluates whether learners show sensitivity to conditional probabilities rather than co-occurrence frequency. In that study the rats failed (Toro & Trobélón, 2005). It is not known whether monkeys are also limited to co-occurrence frequency computations or whether, like human infants, they can compute conditional probability statistics. This failure in rats, however, could be important for explaining why other species do not acquire complex systems like language.

Conditionalized statistics take into account differences in base rates that render first-order statistics less informative for predicting future events. For example, consider a case in which two elements (X and Y) occur frequently but just as often with each other as with other elements, while two other elements (A and B) occur rarely but always with each other. If one simply counted bigram frequency, the number of XY pairs could exceed the number of AB pairs, yet A is more predictive of B than X is predictive of Y. The conditional probability of Y given X and B given A captures this predictiveness better than the frequency of pairs XY and AB does. Interestingly, research on classical conditioning in the rat provides clear evidence of sensitivity to conditional probabilities (Rescorla & Wagner, 1972), but this paradigm places much less demand on memory and computational resources than typical SL paradigms, which require that learners keep track of the conditional probabilities relating many elements at the same time. Again, it is important to note that sensitivity to conditional probabilities does not imply that N-gram frequency of occurrence is unimportant. Highly frequent elements may, for example, serve as anchor points (or filters) that parse the input so that higher-order statistics can be computed over more limited subsets of the data. Several computational models of word segmentation (Swingley, 2005) and form-class learning (Mintz, 2003; Mintz, Newport, & Bever, 2002) use the strategy of operating over only the 200 or 300 most frequent elements.

Another important issue is what use is made of the statistics that are computed from a corpus of input. That is, what decision mechanism operates on those stored statistical values? It seems highly unlikely that statistics computed from
a corpus are retained in memory with sufficient fidelity that microdifferences could be used in making decisions about word boundaries or other properties of the underlying structure (e.g., a transitional probability difference of 0.43 vs. 0.39 meaningful). But given a reliable difference in some computed statistic, is the decision rule based on a local minimum or on a hard threshold? Safran, Newport, & Aslin (1996) referred to “dips” in the transitional probabilities (TPs) at word boundaries and suggested that these dips could serve as a cue to word onsets. However, as noted by Yang (2004), such locally relative dips would not be present for single-syllable words (i.e., there would be low TPs both before and after the single-syllable word). However, a hard threshold (e.g., TPs below some criterion) would serve as a useful segmentation algorithm even for single-syllable words. Given the computational modeling of Swingley (2005), such a hard threshold is a viable mechanism, although to date we have no empirical evidence that such a mechanism actually operates in infants.

A general concern of artificial language (or artificial lexicon) studies is that they may not “scale up” to real corpora. That is, infants (and adults) may successfully use SL mechanisms to solve word segmentation and other problems when the language is extremely small but perhaps not when the problems reflect the size and complexity of real languages. This, of course, is a serious concern, but it may be offset in many cases by the myriad correlated statistical cues to structure that are present in real languages. We certainly recognized this potential problem in Safran, Aslin, & Newport (1996): “Although experience with speech in the real world is unlikely to be as concentrated as it was in these studies, infants in more natural settings presumably benefit from other types of cues correlated with statistical information (p. 1928).”

How Is Statistical Learning Constrained?

The studies conducted since 1996 strongly suggest the existence of a robust SL mechanism in adults, infants, and at least two nonhuman animal species. Given the computational problem of explosive combinatorics (the curse of dimensionality), what enables a SL mechanism to operate without attempting to compute too many statistics (or just the wrong ones, those that mismatch the underlying structure)? Here we consider a set of constraints, some innate and some potentially learned from the input, that allow a powerful SL mechanism to be tractable in finite time.

Preferred Units

One problem for a SL mechanism concerns which basic units, out of the many available, are the ones on which statistical computations should be performed. Safran, Aslin, & Newport (1996) presumed that the unit of analysis for initial word segmentation was the syllable. However, recent work with adults (Newport & Aslin, 2004) showed that statistics that reside at the segment (consonant or vowel) level, in the absence of contrastive syllable statistics, are sufficient for word segmentation. Work in progress (Newport, Weiss, Wonnacott, & Aslin, 2004) suggests that adults and infants in fact rely primarily on segment information or on the alignment of segment and syllable information to solve the word-segmentation problem. When the statistics indicating word boundaries were at the syllable level and not the segment level, both adults and infants failed to segment words from streams of speech. By focusing on a subset of the potential types of units for statistical analysis, the learner reduces the combinatorics and simplifies the SL problem.

Gestalt Principles

A related set of constraints relies on Gestalt principles to bias what is learned. Some elements naturally tend to be linked perceptually, even without any learning process, and statistical relations among these may be most easily learned. For example, Baker, Olson, and Behrmann (2004) conducted a variant of the Fischer and Aslin (2001) studies employing multielement scenes; however, in contrast to Fischer and Aslin, in these studies there was no grid to make clear that each element was an isolated unit prior to learning. In this paradigm, adults are more likely to link together by statistical learning the elements in visual scenes that are connected by thin lines. Another example of a Gestalt constraint in the visual domain comes from Fischer, Scholl, and Aslin (2007). They used dynamic displays in which an object moved behind an occluder and then two objects emerged from the occluder. One object was a perceptually consistent continuation of the preoccluded object's trajectory, while the other was not. Subjects showed a preference for learning the temporal order statistics that conformed to the better continuation—that is, learning the sequence of shapes that appeared as connected.

More relevant to the language domain is a study by Creel, Newport, and Aslin (2004). They presented a sequence of tones as in Safran et al. (1999), but in one condition the tones alternated between two different octave ranges. This induces a percept called auditory streaming (Bregman, 1990) in which attention is bistable between one or the other of the two octave sequences. Creel et al.'s stimuli had strong statistical relations between nonadjacent tones and weaker cues between adjacent tones. When the tones in both streams came from the same octave, adults learned the weaker statistics among temporally adjacent elements; however, when the streams came from different octaves, adults learned the nonadjacent statistics, favoring a grouping of elements within the same pitch range rather than those that were temporally adjacent. In other words, the perceptual bias of auditory streaming constrained SL. Although the foregoing studies show clear evidence for Gestalt constraints on SL, they are not particularly relevant to word segmentation because perceptual similarity among elements is not a reliable cue to words in natural languages.
Social/Attentional Cues

Language typically occurs in a social context in which there are two or more talkers communicating and in which there is some visual information to complement the auditory information. Baldwin (1993) showed that 14-month-olds are more likely to treat a new label as referring to a novel object that is being looked at by the talker. Based on this work, Yu, Ballard, and Aslin (2005) conducted a study of adults’ use of gaze information in a word-segmentation and word-learning task. Learners viewed videotapes of an adult describing the contents of a picture book in Mandarin. In one condition the videotape provided images of the picture book and the pages being turned as the Mandarin speaker described its contents. In the other condition the videotapes also contained information about the talker’s eye movements to the picture book as the pictures were being described. The results showed a clear advantage on both word segmentation and word learning for the adults in the gaze condition over the no-gaze condition. These results suggest that, at least in adults, nonlinguistic cues such as eye gaze can aid in learning to segment speech and to attach sounds to referents.

What Are the Limits of SL?

Like other examples of implicit (unsupervised) learning, SL was initially thought to involve minimal overt attention. This was based on the Saffran et al. (1997) study of preschoolers (and adults) who were not instructed to listen to the streams of speech but nevertheless learned to segment them. Of course, one can never know if learners are occasionally directing their overt attention to the speech streams even though, on average, they are not attending to them. Perhaps an occasional “monitoring” of a speech stream is sufficient to extract the underlying statistics. Toro et al. (2005) recently showed that a dual task reduced the performance of adults on a SL task. A more direct test of the role of overt attention was conducted in the visual domain by Turk-Browne, Jungé, and Scholl (2005). They had adults watch streams of simple visual shapes as in Fiser and Aslin (2002a), but they required their subjects to attend only to shapes in one color by having them look for a rare shape repetition. The shapes in the unattended color required no monitoring. The results showed that only statistics residing in the attended color stream were learned, even if there were intervening shapes in the unattended color.

Another limitation on SL is temporal adjacency, though (as described already) this interacts with other Gestalt principles. Newport and Aslin (2004) created streams of syllables in which the statistics forming word groupings resided in nonadjacent syllables. In these stimuli, the TP from syllable 1 to syllable 3 was 1.0, whereas the TP from syllable 1 to syllable 2, from syllable 2 to syllable 3, and from syllable 3 to syllable 1 of the next word was 0.5. Across a large series of experiments, adults failed to learn the words in these nonadjacent syllable languages. In contrast to these negative results, Peña, Bonatti, Nespor, and Mehler (2002) reported successful learning of nonadjacent syllables under similar conditions, but using a different speech synthesizer, a different set of phonetic elements, and Italian- rather than English-speaking adults. It remains unclear why this discrepancy exists, but repeated attempts in our lab to observe learning of these nonadjacent syllable languages by 8- to 24-month-olds have failed over the past three years. In contrast, word groupings formed from the statistics among nonadjacent phonemic segments (consonants or vowels) are readily learned by adults. In this case, the perceptual similarity of the nonadjacent elements (being all consonants or all vowels) may overcome the preference for adjacency.

A final impediment to SL is the familiarity of the elements themselves. Many studies have demonstrated that statistical relations among speech sounds and tones are easily learned (at least in streams that contain adjacent statistics). However, Gebhart, Newport, and Aslin (2004) reported that statistical groupings among unfamiliar nonspeech sounds were very difficult to learn. It took adults more than 45 minutes of exposure across three sessions to extract the same simple triplet-based statistical structure among adjacent elements that was learned in our initial studies in 2 minutes with speech stimuli. This result is similar to findings on early word learning (Fennell & Werker, 2003; Stager & Werker, 1997; Swingley & Aslin, 2007) in which unfamiliar auditory word forms are much more difficult to associate with a picture of an object than familiar word forms.

The foregoing limits on SL—attention, adjacency, and familiarity—all concern the extraction of information from surface forms. But is SL limited only to surface forms? One of the important aspects of language that is not captured by the SL mechanism we have described so far is transfer from one set of surface tokens to novel tokens of the same underlying type (or category). This has been termed rule learning (RL) by Marcus, Vijayan, Bandi Rao, and Vishton (1999), who showed that 9-month-olds could learn a pattern such as ABB instantiated in 16 different exemplars and then generalize that ABB pattern to novel exemplars. Since SL operates on surface forms, Marcus et al. argued that RL and SL are qualitatively different mechanisms and suggested that RL necessarily involves encoding variables and relations, not the statistical properties of specific elements.

Additional work in the RL paradigm (Gómez & Gerken, 1999; Saffran & Wilson, 2003) provides strong support for the kind of learning with generalization reported by Marcus et al. (1999) and shows that it is not based on perceptual or phonetic similarity of the surface forms. However, evidence of RL does not eliminate SL as a contributor to the extraction and formation of rules. For
example, Gómez (2002), Gómez and Maye (2005), and Mintz (2003) have shown that the distributional properties of the surrounding context affect the formation of a rule (or category). And Endress, Scholl, and Mehler (2005) have shown that repetition of a syllable facilitates rule-based generalizations, especially when repetition occurs at the end of phonological phrases.

More relevant to the distinction between SL and RL is the fact that the RL paradigm differs in an important way from the SL paradigm: The RL paradigm involves strings of finite length (typically three CV or CVC words), whereas the typical SL paradigm involves continuous streams of CV syllables. The pauses that surround finite strings enable the encoding of absolute and relative position information (first element, second element, and so forth) that is lost once a continuous stream of syllables exceeds a dozen syllables. Some of the important differences in learning may arise from this rather than from a qualitative difference of mechanisms.

Clearly, RL operates over categories rather than over the surface forms that serve as the input to SL. But does this imply that RL and SL use a different mechanism? The computation of statistics over categories in RL may involve the same SL mechanism as computation over surface forms. Evidence in tamarins (Hauser, Weiss, & Marcus, 2002) suggests that RL is not unique to humna, and recent evidence (Saffran, Pollak, Seibel, & Shkolnick, 2007) suggests that RL can operate on visual materials (photos of dogs and cats). Thus, despite claims that, unlike SL, RL is unique to spoken language (Fernandes, Marcus, & Little, 2005), it may be more accurate to claim that speech syllables are preferred elements over which RL can operate.

How Might SL Go Awry?

Given the prevalence of SL in studies of normally developing infants, it is natural to ask whether SL may be deficient or delayed in a subset of the general population. For example, perhaps children who exhibit patterns of language delay (e.g., SLI or dyslexia) have difficulty with the earliest phases of language learning. Tests administered in infancy might detect these deficiencies at an age when remediation is effective to enhance long-term outcomes.

A number of features of SL could be susceptible to deficiency or delay. There may be atypical weightings of constraints, such that attention is directed to the wrong units or computations are conducted using the wrong statistics. Another possibility is that the units over which SL is conducted are weakly represented in memory, much like unfamiliar noises in Gebhart et al. (2004), thereby delaying successful SL until additional exposure is obtained.

A more provocative hypothesis is that an early commitment to statistical structure could "block" later SL at higher levels. Support for this hypothesis comes from recent work in both the visual and speech domains using successive presentations of different statistical structures.

Catena, Scholl, and Isola (2005) used the simple successive visual shape paradigm of Rieser and Aslin (2002a) and either preceded or followed a structured stream of shapes with a random stream. Only in the condition where the structured stream came first did adults learn the embedded triplet structure; when the random stream came first, the structure in the subsequent stream was not learned. Gebhart, Aslin, and Newport (in preparation) sequentially presented two different structured streams of speech syllables (two different "languages"), each of which was shown in a baseline experiment to be well learned in 5 minutes of exposure. The two 5-minute streams were presented in immediate succession, without a break, and then a post-test was assessed learning of words versus part-words in each language. Only the first language was learned at above-chance levels (indeed, it was learned as well as when it was presented alone); the second language was not learned. These results suggest that initial extraction of statistical structure inhibits subsequent SL. Indeed, even three times the exposure to the second language was insufficient to bring performance up to the levels of the first language. Interestingly, however, in a follow-up experiment when adults were told there were two languages and were given a 30-second pause between them, performance on both languages was well above chance and similar to performance when either of the languages was presented alone.

CONCLUSIONS

The past decade of research on statistical learning has shown it to be ubiquitous and powerful. SL operates in humans of all ages, in nonhuman species, and in at least three domains (Conway & Christiansen, 2004). Despite the explosive combinatorics of the possible statistics embedded in simple artificial languages or visual scenes, SL solves this problem by employing a set of powerful constraints. Further research will reveal whether these constraints are species and domain specific or if they are universal. It is clear that SL is not sufficient to solve all of the problems necessary for language acquisition. However, it is not yet clear whether SL can account for at least some aspects of rule learning, for example, by operating at the level of categories, or rather whether RL involves a qualitatively different mechanism. Finally, it is possible that an understanding of SL can provide insights into language disorders. A variety of subtle deviations in the constraints on SL could lead to language delays or deficits; exploration of how deviations in SL early in infancy could affect later language development holds the prospect for early diagnosis and remediation of language problems.
The sustained interest in SL stems in part from a broader shift in the field from formal symbolic models of linguistics to probabilistic models that emphasize the distribution of exemplars and the importance of the richness of the input. Yet, to be historically accurate, we never claimed that SL was the only mechanism for solving the word-segmentation problem or that it was sufficient for solving other problems at higher levels of language structure, despite claims on our behalf (Bates & Elman, 1996). A long tradition of structural linguistics (cf. Harris, 1955) and computational linguistics (Charniak, 1993) preceded the fundamental principles of SL as applied to the word-segmentation problem, and in fact these prior investigations were focused on the syntactic parsing problem, which entails considerably more complexity than word segmentation because linguistic categories are, by definition, beyond the surface structure of the input.

Our goals in this chapter are to address four key questions:

1. What is SL, at least as we define it, and over what ages, domains, and species does it operate?
2. How is SL constrained to enable rapid learning to be tractable given the limits of human information processing and the explosive combinatorics of even the simplest language?
3. What are the limits of SL for explaining language acquisition beyond the word-segmentation problem?
4. How might SL go awry in special populations of children who suffer from language deficits?

WHAT IS STATISTICAL LEARNING?

We propose the following three criteria for defining SL. At the most basic level, SL involves the acquisition of structured information from the auditory or visual environment via sensitivity to frequency or probability distributions. Importantly, SL involves no overt reinforcement or direct feedback but rather operates by mere exposure or observation. Finally, in most cases SL involves rapid presentations of stimulus materials and therefore places substantial demands on both short- and long-term memory.

The foregoing definitions of SL provide a context for why it has captured the interest of many researchers, both in language development and in other domains. Something like SL must be how language is acquired. There is no instructor (parental or otherwise) who provides corrective feedback to the young child’s ungrammatical utterances (Brown & Hanlon, 1970; Hirsh-Pasek, Treiman, & Schneiderman, 1984; Wexler & Culicover, 1983). And certainly the word-segmentation problem, as well as other aspects of learning the formal structure of languages, is solved by mere exposure to the native language.

SL also captured the interest of the field because, at first blush, it appears to be so implausible. How does an 8-month-old infant extract from a 2-minute stream of continuous speech, consisting of 540 syllables (> 4 syllables/sec), the higher-order statistics of bisyllable frequency or transitional probability? Even adults, with the aid of paper and pencil, could not keep up with this rapid counting exercise. More importantly, such a tabulation, even if it were possible at slower rates of presentation, would not explain how learners extract the specific statistics that describe the actual underlying structure of the input. There is an infinite number of possible statistics even in this simple example of counting co-occurring syllables (e.g., trisyllables, quadruplets, and so forth, and a huge number of nonadjacent statistics).

The problem of infinite statistics is referred to as the combinatorial explosion problem or the curse of dimensionality. As the number of distinct elements in a set increases linearly, the number of combinations of elements increases exponentially. For example, consider a 10 x 10 array of pixels in a visual image. If each pixel can take on one of eight possible levels of gray (from black to white), there are 8 to the 100th power unique images. Among this vast number of possible images, only a very small fraction of these are actually attested in the natural visual world. A learner confronted with the set of natural images must ignore (or filter out) the much larger set of possible images that are merely noise. Similarly, consider the number of possible words generated by legal combinations of consonants and vowels. In English there are approximately 9,000 legal consonant-vowel-consonant (CVC) words, yet only 11% are actual words. While this has proven useful for psycholinguists who need a large set of nonwords for their research, it illustrates the fact that, like visual images, a language learner must ignore (or filter out) from the possible combinatorics of English phonemes those that do not form lexical items.

Of course, the foregoing examples presume that the learner “knows” the relevant units over which structure is defined (pixels or phonemes). The problem is even more daunting for the naive learner, who must determine which visual features or bits of sound define the relevant units over which statistics should be computed and which features or bits are “noise.” Given infinite time with paper and pencil, a learner could in principle keep track of all possible statistics. But the reality of language and visual processing is that human learners have a finite information processing system that must access rapid streams of speech (4–5 syllables/sec) and complex scenes that occur at the rate of eye movements (2–3 fixations/sec).

How might human learners accomplish the SL tasks given the foregoing impediments? Neither the efficiency of short-term memory in accessing and retaining rapidly presented inputs nor the capacity of long-term memory for storing or computing complex frequency distributions seems plausible, even in adults and certainly not in infants. Yet we know from the psycholinguistics literature that
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ENDNOTES

1. At the time of writing this chapter, Saffran, Aslin, et al. (1996) has been cited 377 times (Web of Science).
2. Transitional probability (Miller & Selfridge, 1950) is a temporally ordered version of conditional probability. It is similar to other conditional statistics such as conditional entropy and mutual information. We make no claim about its uniqueness in accounting for the results of SL; most of our results are equally compatible with these other related conditional statistics.
3. Bonatti, Peña, Nespor, and Mehler (2005) replicated these SL results for nonadjacent consonants but not for nonadjacent vowels. The reason for this discrepancy is currently under study.

REFERENCES


