LSHSS

Tutorial

Reading as Statistical Learning

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Purpose: The purpose of this tutorial is to explain how learning to read can be thought of as learning statistical regularities and to demonstrate why this is relevant for theory, modeling, and practice. This tutorial also shows how triangulation of methods and cross-linguistic research can be used to gain insight.
Method: The impossibility of conveying explicitly all of the regularities that children need to acquire in a deep orthography, such as English, can be demonstrated by examining lesser-known probabilistic orthographic cues to lexical stress. Detection of these kinds of cues likely occurs via a type of implicit learning known as statistical learning (SL). The first part of the tutorial focuses on these points. Next, studies exploring how individual differences in the capacity for SL relate to variability in word reading accuracy in the general population are discussed. A brief overview of research linking impaired SL and dyslexia is also provided. The final part of the tutorial focuses on how we might supplement explicit literacy instruction with implicit learning methods and emphasizes the value of testing the efficacy of new techniques in the classroom. The basic and applied research reviewed here includes corpus analyses, behavioral testing, computational modeling, and classroom-based research. Although some of these methods are not commonly used in clinical research, the depth and breadth of this body of work provide a compelling case for why reading can be thought of as SL and how this view can inform practice.
Conclusion: Implicit methods that draw on the principles of SL can supplement the much-needed explicit instruction that helps children learn to read. This synergy of methods has the potential to spark innovative practices in literacy instruction and remediation provided by educators and clinicians to support typical learners and those with developmental disabilities.

Reading is a skill that must be learned. This learning often begins with the task of reading aloud individual words—a task that can be thought of as learning to detect statistical regularities (also referred to as quasiregularities or probabilities). For example, in English, the letter "m" often denotes the phoneme /m/, but letter combinations containing "silent" letters such as "mb" or "mn" also denote this phoneme as in "thumb," "comb," "hymn," "column," "solemn," and so on. These nondominant mappings can, themselves, be considered regularities rather than random exceptions. Note the complexity of these mappings in that the "mb" and "mn" sequences have different but predictable phonological realizations across syllable boundaries in some longer words like "combined" and "solemnity." Other regularities can be found in the denotation of vowels using nonadjacent dependencies among letters (e.g., the vowels within these consonant frames change in a predictable way when combined with a "silent e": "hat" vs. "hate," "fin" vs. "fine," "mop" vs. "mope"). There are also many regularities in the way that letters are combined within written words—orthotactic or graphotactic regularities (related terms include bigram and trigram frequencies).

Children are given explicit instruction regarding some of these regularities to assist them when they are beginning to "crack the code." Such instruction is vital in the early years of decoding. However, in a language such as English, which has a deep orthography with many-to-many mappings between orthography and phonology rather than one-to-one mappings and complex mappings that depend upon positional and other contextual regularities, it is not possible to convey explicitly all of the regularities that children need to know in order to become skilled readers. Thus, it must be assumed that some regularities are acquired implicitly.

In order to fully appreciate why it is impossible to convey explicitly all of the regularities used during skilled reading, it is helpful to discuss some lesser-known regularities. In the first part of this tutorial, I will outline research on probabilistic orthographic cues to lexical stress in polysyllabic words and nonwords. Converging evidence from corpus analyses, behavioral testing, and computational modeling has revealed a rich source of probabilistic orthographic cues

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to lexical stress that are used in predictable ways, albeit without explicit instruction or conscious awareness. Detection of these kinds of regularities on the part of the reader likely proceeds via a type of implicit learning known as statistical learning (SL). In the second part of this tutorial, I will outline research on the link between individual differences in the capacity for SL relates and variability in word reading accuracy in the general population. I will touch briefly on research on the link between SL and dyslexia and will end the tutorial with discussion of some recent research that has examined how we might supplement explicit literacy instruction with implicit learning approaches. With another paper in the special issue devoted to spelling (Treiman, 2018), the focus in this article is reading. Due to length constraints, I will focus primarily on studies of English, although I include brief mention of other alphabetic orthographies and some nonalphabetic orthographies where appropriate.

Lesser-Known Regularities That Help Us Assign Lexical Stress When Reading Aloud

Lexical stress can be defined as the opposition of strong versus weak syllables or stressed versus unstressed syllables, within polysyllabic words and nonwords. In many languages, lexical stress is an important linguistic feature and must be assigned correctly when speaking and when reading aloud in order to derive meaning. Consider first-syllable stress in a word such as "ZEbra"—if we read this word incorrectly, with stress on the second syllable, the result is the nonsensical "zeBRA." In some languages lexical stress is fixed in that stress always occurs on the first syllable or the last syllable of a polysyllabic word; however, this is not the case in languages such as English where the position of the strong syllable within polysyllabic words is variable. Thus, some disyllabic English words have first-syllable stress (also known as a strong–weak or trochaic pattern of stress) as in "monkey," whereas others have second-syllable stress (also known as a weak–strong or iambic pattern of stress) as in "giraffe." A fascinating question is whether there might be subtle cues in English orthography that guide our assignment of lexical stress during reading.

For decades, most of the research on how orthography maps onto phonology during the reading aloud of individual words and nonwords was based on the reading of monosyllabic stimuli. As monosyllabic stimuli do not have lexical stress, researchers were able to limit their focus to examination of how orthography maps onto segmental phonology. However, as in most languages, the majority of English words are polysyllabic. Thus, examination of how orthography maps onto suprasegmental aspects of phonology, such as lexical stress, became a pressing issue. Understanding how the letters "c-a-t" map onto the monosyllabic word "cat" was not sufficient for understanding different phonological realizations in the reading aloud of the polysyllabic words "caterpillar" versus "catastrophe" and did not shed light on why people tend to assign lexical stress in particular ways when reading aloud polysyllabic nonwords.

A major focus of my collaborative research program has been understanding the assignment of lexical stress during the reading of words and nonwords. Some early research in this area indicated that there might be orthographic cues to lexical stress in the final part of English words (e.g., Kelly, Morris, & Verrekia, 1998; Smith, Baker, & Groat, 1982; Zevin & Joanisse, 2000). However, there had been no large-scale corpus analyses conducted that provided strong evidence regarding the presence of such orthographic cues, and there had been little attention given to the possibility that these cues could be considered probabilistic in nature. Arciuli and Cupples (2006) devised an operational definition of "word ending" (i.e., the rime of the final syllable as in "-ow" from "follow" and "-ard" from "wizard") and conducted a corpus analysis of over 7,000 disyllabic words using the CELEX database (Baayen, Piepenbrock, & Gulikers, 1993). As acknowledged by Arciuli and Cupples (2006), a small proportion of polysyllabic English words do not fit the standard model whereby a rime contains a vowel and any subsequent consonant(s). For example, words like "rhythm" and "bottle" contain syllabic final consonants. For these words, /m/ and /l/, respectively, act as the rime. In a word such as "carry," the final letter serves as a vowel and would be considered the rime. Regardless of any debate about how one might identify the rime of the final syllable in these kinds of words, provision of this definition was an important first step in allowing corpus analyses to be conducted.

Indeed, the corpus analysis revealed evidence that certain combinations of letters are probabilistically associated with certain patterns of lexical stress and that such cues are pervasive in English orthography. For example, the analysis showed that 91% of disyllabic words ending in "–an" and 64% of words ending in "–ure" have first-syllable stress. By contrast, 72% of disyllabic words ending in "–ose" and 86% of words ending in "–uct" have second-syllable stress. An appendix listed 340 of these kinds of word endings and their probabilistic relationship with lexical stress. As an aside, these orthographic cues are also probabilistically related to grammatical category, especially with regard to whether a word is a noun or a verb. This was demonstrated in investigations of disyllables by Arciuli and Cupples (2006) and Kemp, Nilsson, and Arciuli (2009). This was further demonstrated in investigations of trisyllables by Arciuli and Monaghan (2009) and in an fMRI study by Arciuli, McMahon, and de Zubicaray (2012).

Arciuli and Cupples (2006) demonstrated that adults are sensitive to these cues by creating nonwords with particular biasing word endings and examining how adults assign stress when reading these nonwords. Results indicated that adults respond in predictable ways that indicate sensitivity to these cues. They tend to assign first-syllable stress when reading a nonword such as "plosure," which has an ending that is strongly associated with first-syllable stress in English words. By contrast, adults tend to assign second-syllable stress when reading a nonword, such as "feduct," which has an ending strongly associated with second-syllable stress in English words.

Arciuli and Paul (2012) examined sensitivity to these probabilistic orthographic cues to lexical stress in adolescents with autism spectrum disorders versus typically developing peers (matched on age, verbal IQ, oral language ability, and reading ability). Using the nonword stimuli from Arciuli and Cupples (2006), they demonstrated that adolescents with autism do not assign lexical stress in predictable ways like their typically developing peers. Among possible explanations, Arciuli and Paul (2012) hypothesized that this might be due to a lack of sensitivity to probabilistic orthographic cues, which may be related to difficulties with implicit forms of learning such as SL. For discussion of the handful of studies that have examined whether SL might be atypical in (some) individuals with autism, see Arciuli (2017).

Following the suggestion by Kelly (2004) that the initial part of words might also hold cues to lexical stress, a corpus analysis of the CELEX database by Arciuli and Cupples (2007) led to the discovery of probabilistic orthographic cues to lexical stress in "word beginnings" (i.e., all letters up to and including the first vowel as in "fo–" from "follow" and "wi–" from "wizard"). By creating nonwords with neutral endings and beginnings that were biased to either first or second-syllable stress, Arciuli and Cupples again demonstrated adults' sensitivity to these kinds of cues during reading. It was noted that, although participants assigned lexical stress in predictable ways, these tendencies appeared to be less strong than in the previous study of word endings.

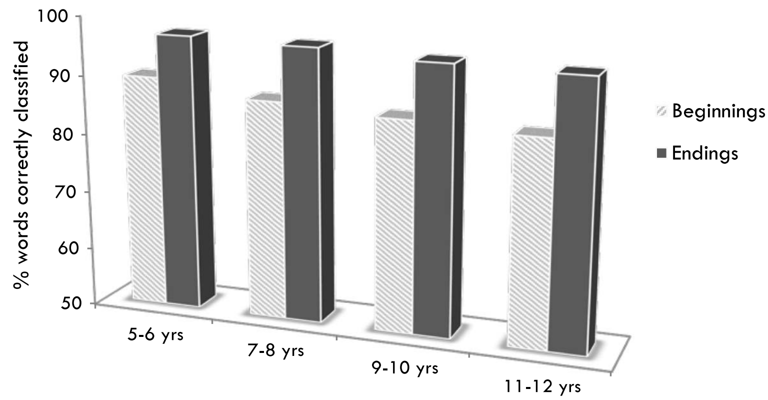
Subsequent cross-linguistic research has revealed pervasive probabilistic orthographic cues to stress in the initial and final parts of polysyllabic words in large-scale corpus analyses of Italian, Greek, Dutch, Spanish, and German, as well as English, the position and size of which (sometimes termed "granularity") differ across languages (Monaghan, Arciuli, & Seva, 2016). It is noteworthy that the analysis of English, much larger than that conducted by Arciuli and Cupples (2006)—and with the addition of trisyllabic words—confirmed the rich source of information contained within "word endings" as defined by Arciuli and Cupples (2006). Monaghan et al. (2016) analyzed over 20,000 disyllabic words and over 14,000 trisyllabic words. The results showed that "word endings" were more accurate in classifying words correctly according to stress patterns than "word beginnings" and were more accurate when compared with alternative analyses using just the last consonant, just the last vowel, or just the last letter as a cue to stress. However, each of these alternative orthographic units contained fairly reliable cues to stress indicating the presence of multiple cues. Subsequent behavioral and electrophysiological studies have demonstrated participants' sensitivity to these kinds of probabilistic orthographic cues in languages other than English (e.g., see studies of Italian, Greek, and Russian by Burani & Arduino, 2004; Grimani & Protopapas, 2017; Jouravlev & Lupker, 2014, 2015; Sulpizio & Colombo, 2017, among others).

Following identification of an abundant source of probabilistic orthographic cues in word beginnings and word endings and demonstration of adults' sensitivity to these cues, the next step in my collaborative research program was to focus on children and provide an account of how children learn to assign lexical stress when reading aloud. The account reported by Arciuli, Monaghan, and Seva (2010) used triangulation of methods: corpus analyses to investigate whether probabilistic orthographic cues to stress are present in children's age-appropriate reading materials, behavioral testing of 5- to 12-year-olds to examine children's sensitivity to these cues at different ages, and computational modeling to explore incremental and implicit learning of these cues based on iterative training of the model with age-appropriate input.

To progress a truly developmental account of stress assignment during reading, it was critical to demonstrate that children are exposed to these kinds of probabilistic orthographic cues in their reading materials. Using the Educator's Word Frequency Guide database (Zeno, Ivens, Millard, & Duvvuri, 1995), our corpus analyses of 2,959 disyllabic words in reading materials designed for 5- to 6-year-olds, 3,814 disyllabic words in materials for 7- to 8-year-olds, 4,430 disyllabic words in materials for 9- to 10-year-olds, and 4,594 disyllabic words in materials for 11- to 12-year-olds confirmed the presence of probabilistic orthographic cues to lexical stress in children's reading materials (Arciuli et al., 2010). Importantly, the corpora for each age group included both monomorphemic and multimorphemic words. Results revealed that the percentage of words with first-syllable stress gradually decreased in the reading materials for older children (conversely, the percentage of words with second-syllable stress gradually increased in the reading materials for older children). Of particular interest, discriminant analyses revealed that cues in "word endings" were more reliable in classifying disyllabic words correctly based on their pattern of lexical stress than "word beginnings" in the reading materials for every age group. This is demonstrated in Figure 1, which represents some of the data reported by Arciuli et al. (2010). The cues appear to be quite strong; the vast majority of disyllabic words in children's reading materials can be classified correctly as having either first-syllable stress or second-syllable stress solely on the basis of the letter sequence in the final part of the word as defined by Arciuli and Cupples (2006).

As in the earlier studies with adults, nonwords were created to test children's sensitivity to these probabilistic orthographic cues. Behavioral results from the testing of a large sample of 186 children demonstrated that, as exposure to written language increases with age, sensitivity to these probabilistic orthographic cues to lexical stress—particularly those present in "word endings"—increases. The computational modeling component of this research, which advanced earlier modeling work on adult data by Ševa, Monaghan, and Arciuli (2009), utilized a single-route feed-forward connectionist architecture based on the principles

Figure 1. Results of discriminant analysis showing the percentage of disyllabic words that can be correctly classified according to stress pattern on the basis of either word beginnings or word endings in the reading materials for four age groups (token analysis). yrs = years.



of SL. The developmental modeling by Arciuli et al. (2010) demonstrated gradual learning of the regularities between orthography and lexical stress in a way that closely simulated the child data. Note that it was not necessary to specify units for these computational models to learn from, such as "word beginning" or "word ending." This is because connectionist models are able to learn the regularities.

Computational Modeling of Stress Assignment Based on Principles of SL

Computational modeling, in combination with behavioral data, has long been recognized to be a valuable tool that allows us to test hypotheses about a range of mental processes including reading (Seidenberg, 2005). Connectionist models are, by design, dynamic systems, which are able to learn by extracting statistical regularities from the input presented to them. For an account of the history of connectionism and links with deep learning and Bayesian approaches, see the special issue edited by Mayor, Gomez, Chang, and Lupyan (2014).

For many years, research on the computational mechanisms of reading aloud was devoted to comparing connectionist approaches where the model learns regularities versus alternative rule-based approaches where predetermined rules are built into the model (e.g., Coltheart, Rastle, Perry, Langdon, & Ziegler, 2001; Harm & Seidenberg, 2004; Plaut, McClelland, Seidenberg, & Patterson, 1996; Seidenberg & McClelland, 1989; Zevin & Seidenberg, 2006). This comparison is sometimes referred to as the parallel distributed processing approach versus the symbolic or boxes and arrows approach. As mentioned, research effort was primarily focused on monosyllabic stimuli (but see Chateau & Jared, 2003; Jared & Seidenberg, 1990; Taft, 1992; Yap & Balota, 2009).

In one of the first attempts to model the reading aloud of polysyllabic stimuli, Rastle and Coltheart (2000) devised a rule-based algorithm for stress assignment as part of the nonlexical route within the dual-route cascaded model of reading. The algorithm involved searching a letter string to identify morphemes using a prespecified set of 54 prefixes and 101 suffixes gleaned from Fudge (1984). The algorithm also incorporated consultation of a database for information concerning whether each affix that had been identified carried stress or not (also from Fudge, 1984). The algorithm was able to simulate some aspects of stress assignment in adults' reading but did not shed light on how such a system is acquired. How do we learn what constitutes a prefix and what constitutes a suffix (e.g., why is "ee" a suffix in "mentee" but not in "coffee")? How do we acquire knowledge pertaining to how specific prefixes and suffixes correspond with lexical stress? Why would this kind of stored lexical knowledge relating to morphology be present in a nonlexical route? These kinds of issues presented problems in terms of plausibility, and later dual-route models that have tackled polysyllabic word reading have abandoned this approach and instead incorporated connectionist principles (e.g., CDP++ model: Perry, Ziegler, & Zorzi, 2010).

A recent megastudy by Mousikou, Sadat, Lucas, and Rastle (2017) reported on data from 41 adults who each read aloud 915 polysyllabic nonwords (over 37,000 reading aloud responses in total). That study was designed to compare three computational models in their ability to simulate this adult human data. In terms of simulating stress assignment, the models that were compared were the rule-based algorithm by Rastle and Coltheart (2000), the connectionist CDP++ model by Perry et al. (2010), and the connectionist model based on my collaborative research referred to in the megastudy as the SMA09 model by Ševa et al. (2009). Results showed that the two connectionist models outperformed the rule-based model: "The SMA09 network was the most successful model in capturing human performance on stress assignment, followed by the CDP++ model, thus providing support for a statistical-learning approach to relating spelling to stress in disyllabic reading aloud" (Mousikou et al., 2017, p. 188).

Having researched these lesser-known statistical regularities in written language, I became increasingly interested in the implicit learning mechanism known as SL that is thought to underpin sensitivity to these kinds of regularities. In particular, I wanted to investigate whether individual differences in the capacity for SL might be linked with variability in reading proficiency. Aware that there are multiple factors that contribute to variability in reading proficiency, I wondered whether SL might be one of these.

Exploring Human Capacity for SL

In its broadest sense, SL refers to the ability to detect regularities. It has been associated with implicit learning, procedural learning, motor learning, sequence learning (adjacent and nonadjacent dependencies), and serial order learning. The "statistical" in the term SL refers to specific types of regularities, such as the probabilistic relations outlined above. Some studies have focused on whether SL should be classified as either domain-general or domain-specific, but the field seems to be moving toward a realization of the paradoxical nature of SL—it appears to have attributes of both generality and specificity (Frost, Armstrong, Siegelman, & Christiansen, 2015; Schapiro & Turk-Browne, 2015). See also the linguistic entrenchment hypothesis put forward by Siegelman, Bogaerts, Elazar, Arciuli, and Frost (2018), which suggests that the nature of stimuli used in SL tasks is important when thinking about this paradox. Another feature of earlier studies was investigation of whether SL simply reflects general ability or intelligence, sometimes referred to as a *g* factor—a number of studies have suggested that SL is separable from a *g* factor (e.g., Conway, Baurnschmidt, Huang, & Pisoni, 2010; Kaufman et al., 2010; Kidd, 2012; Kidd & Arciuli, 2016; Siegelman & Frost, 2015).

Over the years, a number of different methods of assessing SL have emerged. Well-established paradigms that examine the ability to detect sequential statistical regularities include the classic triplet task (Saffran, Aslin, & Newport, 1996), the artificial grammar learning (AGL) task (A. S. Reber, 1967), the serial reaction time (SRT) task (Nissen & Bullemer, 1987), and the Hebb repetition task (Hebb, 1961). These tasks and the variations of these tasks that have subsequently been developed differ in multiple and significant ways. For example, there is great variation in terms of the instructions provided to participants, the modality in which regularities are presented, stimulus presentation times, the complexity of the regularities to be learned, and the number of times participants are exposed to the regularities to be learned. In addition, the way that learning is measured differs widely in terms of whether learning is measured as it is happening or after learning has taken place, whether responding draws heavily on motor processes or not, whether responding requires explicit judgements or not, and whether dependent variables relate to reaction times, error rates, or other neurophysiological measures.

Contemporary theorizing views SL as being composed of multiple components, processes, and networks—a kind of emergent property emanating from information processing and memory activities in the brain (e.g., Arciuli, 2017; P. J. Reber, 2013; Thiessen, Kronstein, & Hufnagle, 2013). As such, it may be that different SL tasks draw on particular underlying components more strongly than others. We have yet to identify the specific components of SL, and we do not fully understand how commonly used SL tasks map on to these components. In line with renewed interest in the reproducibility of psychological research (e.g., Hedge, Powell, & Sumner, 2017), the reliability of SL tests has become a point of consideration for many researchers. However, a comprehensive understanding of the psychometric properties of all the different types of SL tasks is still some way off.

Such endeavors are currently being pursued by researchers in the field. The following sections provide an overview of some initial explorations of a possible link between SL and reading in the general population and a possible link between impaired SL and dyslexia, respectively.

Is the Capacity for SL Linked With Reading Ability in the General Population?

The first study of whether individual differences in the capacity for SL relate to variability in reading proficiency in the general population was conducted by Arciuli and Simpson (2012), who utilized a visual SL task created earlier by Arciuli and Simpson (2011). Arciuli and Simpson (2011) initially used this SL task to explore the (im)mutability of SL in a large sample of 183 children aged 5–12 years. Among other findings, Arciuli and Simpson (2011) found that visual SL increased with age during childhood, a result subsequently independently replicated by Raviv and Arnon (2017), who used a similar visual SL task. Age-related issues are revisited later in this article in the section on dyslexia.

The SL task used by Arciuli and Simpson (2011, 2012) is a version of the classic triplet paradigm originally devised to examine infants' ability to learn auditorily presented sequences of syllables (Saffran et al., 1996). Following adaptations of the triplet task using visually presented stimuli in adult studies (e.g., Brady & Oliva, 2008; Fiser & Aslin, 2001; Turk-Browne, Jungé, & Scholl, 2005), Arciuli and Simpson (2011) created a child-friendly task of SL using unfamiliar cartoon-like characters described as aliens.

This SL task is composed of a familiarization phase, which includes a cover task, followed immediately by a surprise test phase. At the beginning of the familiarization phase, participants are provided with a backstory that explains the purpose of the cover task. They are told that they will be undertaking a computer game where aliens from different planets are queuing to enter a spaceship—their task is to detect when two aliens from the same planet appear together (i.e., one after the other) by pressing a button on the keyboard as quickly as possible. Not all SL tasks include a cover task, but we thought it important to be able to provide a backstory concealing the true purpose of the task while also encouraging children to attend to the visual stimuli during familiarization.

As reported in previous studies that have used this SL task, 12 alien stimuli are grouped into four base triplets: ABC, DEF, GHI, and JKL (see Figure 2 for examples of stimuli; see Appendix of Arciuli & Simpson, 2011, for the full set of stimuli). Each base triplet is presented 24 times during familiarization. For six of the 24 instances, one alien character is presented twice in a row (constituting the cover task). The repetitions are counterbalanced among the aliens within the triplet so that there are no cues to triplet boundaries (e.g., for triplet ABC, there are instances of AABC, ABBC, ABCC). Following the constraints reported by Turk-Browne et al. (2005), triplet order is randomized after the following constraints—no repeated triplets (i.e., no instances of ABCABC) and no repeated pairs of triplets (e.g., ABCDEFABCDEF).

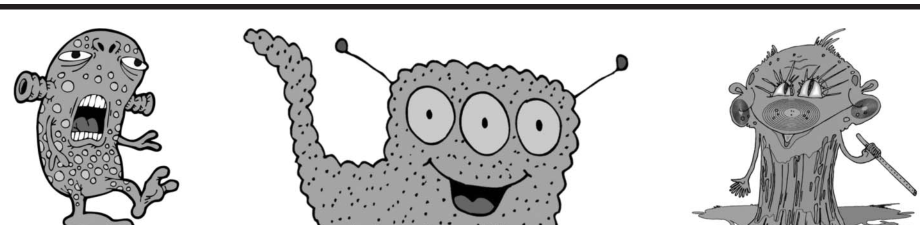
In the surprise test phase, the learning of the sequences of aliens that comprise the base triplets is assessed via 64 forced choice trials where base triplets are pitted against foil triplets. Aliens in the foil triplets never appeared together in sequence in the familiarization phase (AEI, DHL, GKC, JBF). On each trial, participants are prompted to identify which of the two triplets had appeared previously during familiarization without time limits on responding. A percent correct score for the 64 trials is obtained. This is a high number of trials by comparison with some other SL tasks, a notable strength of the task design in terms of ensuring reliability.

In examining the link between SL and reading ability, Arciuli and Simpson (2012) used this visual SL task alongside a standardized test of word reading accuracy (Wide Range Achievement Test 4: Wilkinson & Robertson, 2006). The results revealed a modest positive relationship between individuals' capacity for SL and reading proficiency in children and also in adults, even after age and attention (correct hits during the cover task) were taken into consideration. Moreover, results demonstrated that variables such as phonological working memory and nonverbal IQ did not mediate the relationship between SL and reading ability in a subset of the adults that were recalled for follow-up testing. It has been shown that, unlike some other tasks of SL, tasks that utilize nonverbal visual stimuli within the classic triplet paradigm have high reliability—Cronbach's alpha of .79 for Arciuli and Simpson's alien task described here (Siegelman et al., 2018). A link between SL and reading accuracy was observed using the same alien task with a sample of Norwegian children after taking into account a range of cognitive and linguistic factors including IQ (Torkildsen, Arciuli, & Wie, 2018). However, in a subsequent study where a different version of this visual SL task was used, alongside an auditory version, results indicated that auditory rather than visual SL was linked with English-speaking children's reading ability after controlling for IQ (Qi, Sanchez Araujo, Georgan, Gabrieli, & Arciuli, 2018).

Another individual differences study demonstrated a link between the capacity for SL and variability in reading proficiency in adults learning to read the semi-transparent orthography of Hebrew as a second language (Frost, Siegelman, Narkiss, & Afek, 2013). It has been hypothesized that there may be a weaker link between the capacity for SL and variability in reading proficiency in a shallow orthography such as Spanish presumably because regularities can be conveyed explicitly (Nigro, Jiménez-Fernández, Simpson, & Defior, 2015). Longitudinal research would be invaluable in complementing the correlational research conducted to date (Arciuli & Torkildsen, 2012). Aside from studies of individual differences that compare performance on independent tests of SL and reading, there is research showing that SL plays a role in learning to read in other orthographies such as Chinese (He & Tong, 2017a; Yin & McBride, 2015, 2018).

As discussed by Arciuli and Simpson (2012), the link between SL and reading ability could be both direct and indirect. Direct effects could operate via sensitivity to the kinds of probabilistic orthographic cues outlined earlier in this tutorial along with many other probabilistic cues. Indirect effects could operate via a link between SL and other skills known to be related to reading ability. For instance, among a number of studies on the relationship between SL and vocabulary, an early individual differences study by Evans, Saffran, and Robe-Torres (2009) found a link between children's capacity for SL and their vocabulary (in children with specific language impairment as well as their typically developing peers). There was no link between SL and nonverbal intelligence. Spencer, Kaschak, Jones, and Lonigan (2015) found a link between individual differences in SL and variability in several literacy-related skills including vocabulary in typically developing children. Kidd and Arciuli (2016) used the visual SL task from

Figure 2. Examples of cartoon characters used by Arciuli and Simpson (2012). Although the figures are presented in color during experiments, they are depicted in black and white here.



Arciuli and Simpson (2011, 2012) and found a link between individual differences in children's SL and their grammatical processing even after a variety of cognitive and linguistic variables, including nonverbal intelligence, were taken into account. This link may assist reading at sentence level. However, grammatical processing was tested using a picture-pointing task in that previous study and has not yet been tested in the context of reading.

Is There a Link Between SL and Dyslexia?

Given the focus on reading in this article, an obvious question is whether there is a link between SL and dyslexia. Although it is likely that deficits in phonological processing play a significant role in dyslexia (e.g., Vellutino, Fletcher, Snowling, & Scanlon, 2004), difficulties in other areas might also contribute to this disorder (e.g., Gathercole, Alloway, Willis, & Adams, 2006; Nicolson, Fawcett, Brookes, & Needle, 2010; Wolf & Bowers, 1999, among others). SL might be one of these other areas of difficulty for (at least some) individuals with dyslexia. Indeed, a meta-analysis of SRT studies by Lum, Ullman, and Conti-Ramsden (2013) found that individuals with dyslexia show impaired SL compared to controls. However, the link appeared to be age-related with smaller effects in older participants. A meta-analysis of AGL studies by Witteloostuijn, Boersma, Wijnen, and Rispens (2017) came to a similar conclusion about an age-related link between SL and dyslexia, although they also raised the issue of publication bias, which may favor statistically significant group differences over null effects.

In line with a multicomponent view of SL (e.g., Arciuli, 2017), it may be that particular populations, and individuals within populations, differ in the efficiency of particular components that underpin SL. As noted earlier, SL tasks may differ in how they draw upon the underlying components of SL. This should be taken into account when thinking about relative strengths and weaknesses in individuals with dyslexia. For instance, although Henderson and Warmington (2017) found that English-speaking adults with dyslexia performed similarly to a control group on an SRT task, this was not the case on the Hebb repetition task. Other studies have demonstrated that the nature of the regularities in AGL tasks and the way that AGL tasks are administered can shed light on learning differences between speakers of Hebrew with and without dyslexia (e.g., the study of children by Schiff, Katan, Sasson, & Kahta, 2017; the study of adults by Schiff, Sasson, Star, & Kahta, 2017). Using an SRT task, He and Tong (2017b) showed that the number of times Chinese children with dyslexia were exposed to regularities affected SL performance; SL was impaired after a small number of exposures but unimpaired after a large number of exposures.

In summary, there is evidence to suggest that individuals with dyslexia exhibit atypical SL, depending upon task parameters. However, the link between SL and dyslexia appears to be complex—more research is needed before we can draw firm conclusions. Future research endeavors designed to explore the link between SL and dyslexia ought to consider the role of participant-related variables, such as age, as well as numerous task-related variables. Moreover, there is variability in reading proficiency among individuals with dyslexia just as there is among individuals without dyslexia. This variability is almost certainly due to a number of factors, one of which may be SL. A move away from group comparisons (dyslexia group vs. control group) toward an individual differences approach may be fruitful in discovering the extent to which SL contributes to this variability (e.g., Gabay, Thiessen, & Holt, 2015). An individual differences approach may also be helpful in addressing methodological issues relating to the way that dyslexia is diagnosed across studies that focus on a single language and across studies that focus on different languages.

Supplementing Explicit Literacy Instruction With Implicit Learning Techniques

A number of recent studies have examined the efficacy of implicit learning approaches for enhancing literacy. Rather than being designed to replace explicit instruction, these techniques can be used to supplement explicit instruction. Of particular interest to clinicians and educators are studies that have tackled implicit learning in a classroom setting.

One of the first studies to embrace implicit methods that draw on the principles of SL in order to facilitate literacy acquisition in a classroom setting was conducted by Apfelbaum, Hazeltine, and McMurray (2013). These researchers conducted a study with 224 English-speaking first graders to determine whether children could learn regularities through exposure to words that embody certain regularities in computer tasks. Specifically, children were exposed to regularities concerning the mapping between graphemes and phonemes for vowels over several days. The goal was for children to learn "a" in "bat," "i" in "bit," "o" in "bot," "ai" in "bait," "ea" in "beat," and "oa" in "boat" via six implicit learning tasks (e.g., the "Find the Word" task presented a word aurally and asked children to find that word among eight written alternatives). Children were assigned to one of two groups, which reflected whether consonant frames were variable or similar in the learning tasks. On the implicit learning tasks, children were given multiple attempts and feedback about accuracy but were not given any instruction regarding the regularities. Results demonstrated that children were able to learn these kinds of regularities implicitly. A key finding was that variable consonant frames led to greater learning. Such results highlight the value of considering principles of SL when designing literacy resources for clinical and educational use.

In fact, a number of other studies have demonstrated implicit learning of particular statistical regularities in orthographic input (e.g., Chetail, 2017; Pacton, Perruchet, Fayol, & Cleeremans, 2001), and an increasing number of studies demonstrate the efficacy of incidental learning procedures on broader reading and spelling outcomes (e.g., Protopapas et al., 2017; Tamura, Castles, & Nation, 2017). It would be interesting to compare the efficacy of these different techniques in classroom-based research. Furthermore, the studies mentioned in this section on instructional techniques have been conducted with typically developing children and adults. It would be valuable to utilize some of these techniques in research involving children with developmental disabilities who are struggling with literacy acquisition to ascertain whether gains can be made.

Conclusion

The argument presented in this tutorial is that reading can be thought of as learning statistical regularities. To illustrate the impossibility of conveying explicitly all of the regularities that children need to acquire in a deep orthography such as English, this tutorial has provided discussion of lesser-known regularities such as probabilistic orthographic cues to lexical stress. Converging evidence that detection of these kinds of probabilistic orthographic cues likely proceeds via a type of implicit learning known as SL has been outlined. I have reviewed research on how individual differences in the capacity for SL are linked with variability in word reading accuracy in the general population and provided a brief overview of research linking SL and dyslexia. I have completed this tutorial with a review of some research examining how we might supplement explicit literacy instruction with implicit learning methods and emphasized the value of classroom-based research.

Viewing reading as an exercise in learning statistical regularities can inspire innovative methods of literacy instruction and remediation that will enable educators and clinicians to better support all children, both typical learners and those with developmental disabilities, when they are learning to read. This approach parallels innovations in practices that support oral language acquisition (e.g., Alt, Meyers, & Ancharski, 2012; Alt, Meyers, Oglivie, Nicholas, & Arizmendi, 2014).

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