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Integrating statistical learning into cognitive science

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ABSTRACT

Over the last two decades statistical learning (SL) has evolved into a key explanatory mechanism underlying the incidental learning of regularities across different domains of cognition, such as language, visual and auditory perception, and memory. Yet SL has mainly been investigated as an independent research area, separated from the primary study of the relevant cognitive domains. The aim of this special issue is to foster a bilateral integration of SL research with cognitive science: not only should domain-relevant evidence about the complexity of real-world input become more tightly integrated into SL research, but non-SL studies should also carefully consider the nature and range of statistical regularities that may affect learning and processing in a given domain. Four papers on reading in this volume demonstrate that such integration can lead to a better understanding of reading, while also revealing the complexity and abundance of different statistical patterns present in printed text. Moving beyond disciplinary boundaries has the promise to broaden the focus of SL research beyond simple artificial patterns, to examine the rich and subtle intricacies of real-world cognition. A final paper on the neurobiological underpinnings of SL and the consolidation of learned statistical regularities further illustrates what might be gained from a better integration of SL and memory research. We conclude by discussing possible directions for taking an integrative approach to SL forward.

Statistical learning (SL), broadly defined as the learning from the statistical properties of sensory input across time and/or space, has become a major theoretical construct in cognitive science. While the concept of SL was originally taken to provide an experience-based account of spoken language processing and acquisition (Saffran, Aslin, & Newport, 1996; Aslin, Saffran, & Newport, 1998; and see Romberg & Saffran, 2010 for a review), SL has evolved into a primary explanatory mechanism underlying the incidental learning of most, if not all, regularities in our environment (e.g., Frost, Armstrong, Siegelman, & Christiansen, 2015; Turk-Browne, 2012). The important role of SL in cognitive science stems then from the wide range of basic and higher-order cognitive functions that it subserves, including amongst others, visual and auditory perception, event processing, motor planning, social cognition, face recognition, categorization, syntax acquisition, semantic memory and reading. Note, however, that each of these different domains of cognition is characterized by different types of regularities and probably implicates different types of SL computations (e.g., Arciuli, 2017; Siegelman, Bogaerts, Christiansen, & Frost, 2017; Thiessen, Kronstein, & Hufnagle, 2013). Importantly, the complexity of the regularities in a given domain, be it spoken languages, printed texts, or visual scenes, often significantly differs from the simplified learning problems that are explored in typical SL experiments, which typically involve repeating a small number of artificial patterns at uniform probabilities over just a few minutes. Hence, for SL to establish itself as a fundamental construct of learning and development across cognition, evidence from a wide range of domains should be considered and integrated with SL research (e.g., Krogh, Vlach, & Johnson, 2013; and see Frost, Armstrong, & Christiansen, 2019, for a recent critique and discussion). In the same vein, the investigation of different cognitive functions would benefit from scrutinizing the nature and range of statistical regularities that characterize the input they operate on, as well as the specific computations involved in processing, encoding and retaining these regularities. Fostering such bilateral integration is the central aim of this special issue.

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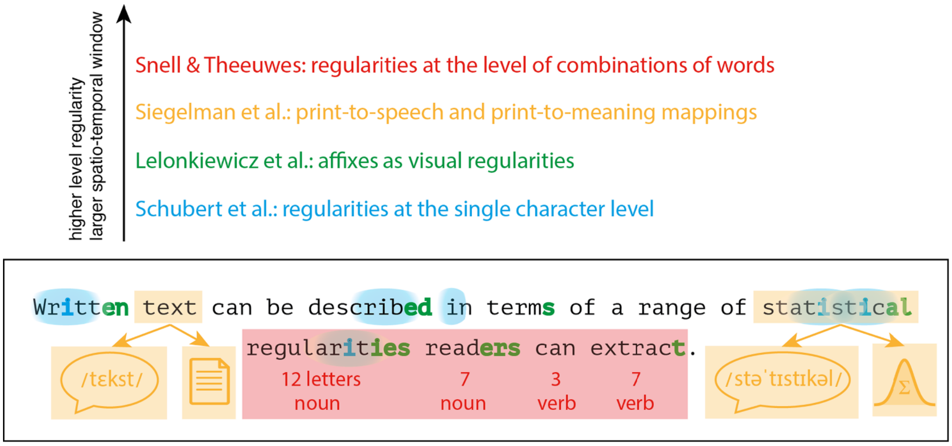

Fig. 1. Different levels of regularities in printed input that are addressed in the special issue.

SL and reading: A case study that reveals new research frontiers

Four papers in the present volume focus on the integration of SL and reading. This offers a unique opportunity to explore the potential breadth and depth of novel theoretical questions that can arise from an integrative approach, even for a cognitive function such as reading, which has been the focus of extensive investigation for decades. The downside of artificially splitting up research areas within psychology is indeed well reflected in the study of reading. In spite of substantial evidence linking reading performance to visual SL abilities (e.g., Arciuli & Simpson, 2012; Chetail, 2017; Frost, Siegelman, Narkiss, & Afek, 2013), of the thousands of studies investigating word perception, literacy acquisition, or eye-movements of proficient readers, very few have harnessed SL research to examine how computations of regularities in the visual system shape our abilities for processing print. Interestingly, scientific studies of reading have traditionally focused on a subset of statistical regularities that characterize writing systems. These include letter-sound regularities (e.g., Castles, Rastle, & Nation, 2018; Frost, 1998; Harm & Seidenberg, 2004; Ziegler & Goswami, 2005), orthographic regularities such as double letters (e.g., Cassar & Treiman, 1997; Pacton, Perruchet, Fayol, & Cleeremans, 2001), and letter-meaning regularities through morphological structure (e.g., Bertram & Hyönä, 2003; Ulicheva, Harvey, Aronoff, & Rastle, 2020; and see Rastle, 2019 for a review). However, fundamental questions remain: *what is the full scope of regularities that are present in written input, and drive individual variance of reading proficiency? Can other "hidden" regularities be identified in corpora of printed text? If so, which of these regularities do proficient readers actually assimilate to increase reading efficiency? And how precisely do the learned orthographic regularities, accumulated across experience, assist reading proficiency?* These are fundamental issues, and a comprehensive theory of reading would be incomplete without addressing them. The four papers on reading in the present volume take an important step in this direction: they directly address some of these questions, and they do so in very different ways. They explore different levels of the statistical structure that is available in print, and they gather evidence through a range of methods such as computational modeling, behavioral experimentation, and database analyses of ocular movements during reading.

Schubert, Cohen and Fischer-Baum's rephrasing of a quote from Firth (1957)—"you shall know a letter by the company it keeps" (Schubert, Cohen, & Fischer-Baum, 2020, p. 2)—nicely summarizes their work, quantifying the information that the text environment carries about the individual characters in a particular orthography. Employing methods from distributional semantics, they modeled the contextual similarity among alpha-numeric characters in a large text corpus and show that this similarity captures key aspects of orthographic knowledge such as letter identity, consonant–vowel status and case (i.e., lower vs. upper case).

Moving beyond single letters, the hybrid SL-psycholinguistic paradigm by Lelonkiewicz, Ktori and Crepaldi (2020) provides a direct test of readers' ability to pick up on chunks of artificial letters at final and initial word positions, mimicking affixes in real language. Their findings suggest that, in a learning context devoid of semantics, a purely visual language-agnostic learning mechanism is able to extract morpheme-like regularities.

Rather than using an artificial task to estimate SL abilities, the work by Siegelman et al. (2020) took on the challenge of studying SL in the "real world" of reading acquisition. Inspired by the triangle model of reading (Plaut, McClelland, Seidenberg, & Patterson, 1996; Seidenberg & McClelland, 1989), they related children's reading aloud behavior to their reliance on print-speech regularities versus print-meaning associations. Poor readers are shown to have a remarkably smaller effect of print-speech consistency yet a larger effect of print-meaning associations, suggesting a division of labor in the reading system that is tied to reading proficiency.

Considering a larger temporal window of learning, Snell and Theeuwes (2020) provide evidence that repeatedly encountering certain word length combinations and syntactic structures within a novel leads to fewer and shorter fixations, and fewer corrective saccades. This work reveals a role of SL within naturalistic reading processes. Given the availability of a large corpus of monolingual and bilingual naturalistic reading behavior (Cop, Dirix, Drieghe, & Duyck, 2017), the paper raises intriguing possibilities for readily testing theories regarding the relative contributions of regularities at different levels (characteristic of either the language or the novel context) and cross-linguistic differences.

While Schubert and her colleagues focus on regularities at the level of orthographic alpha-numeric characters, Lelonkiewicz et al. examine morphological regularities at the grain-size of affixes, Siegelman et al. focus on print-to-speech and print-to-meaning mappings, and Snell and Theeuwes focus on regularities at the level of word combinations. Collectively, these papers reveal the wide range of different types of regularities that are simultaneously present at different levels (i.e., varying spatio-temporal windows) in written input, as depicted in Fig. 1. This raises a set of novel and intriguing research questions for future investigation: *Does the presence of regularities at a lower level assist or hinder the learning of regularities at a higher level? Or, alternatively, does the presence of higher-level regularities assist or hinder the learning of low-level regularities? And, more generally, how are the multiple levels of regularities in the input learned and integrated to form predictions regarding the incoming information?* These questions emphasize the gap between studying SL with miniature artificial language experiments that isolate a singular regularity and the complexity of real-life environments.

The present set of papers also offers novel methods for quantifying the regularities in print (e.g., model-derived similarities, extent of vowel surprisal), along with empirical evidence regarding the sensitivity of learners to these regularities as reflected in different experimental paradigms and behaviors (e.g., familiarity to artificial strings, naming, eye-movements). As such, the present volume provides a deeper understanding of the range of statistical structures that are embedded in printed texts, and the precise role or SL in assimilating them. We should note that SL abilities have been linked to reading performance through correlational research (e.g., Arciuli & Simpson, 2012; Frost et al., 2013; Misyak & Christiansen, 2012; Pavlidou & Bogaerts, 2019; Qi, Sanchez Araujo, Georgan, Gabrieli, & Arciuli, 2019), and through the study of reading impaired populations (see Bogaerts, Siegelman, & Forst, in press; Schmalz, Altoè, & Mulatti, 2017, for reviews). However, such studies have often been vague regarding the mechanistic underpinning of the revealed associations (see Schmalz, Moll, Mulatti, & Schulte-Körne, 2019; Siegelman et al., 2017; and Bogaerts et al., in press, for discussions). A tighter integration between SL and reading research, therefore, has the promise of providing better and more precise theories of how reading is shaped by a variety of SL computations.

Whereas this volume does not include empirical evidence for the range of regularities relevant to other aspects of cognition, the present “case study” of SL and reading demonstrates the potential impact of integrating SL into other domains such as, say, face perception (Oruc, Balas, & Landy, 2019), scene viewing and object identification (Graham & Redies, 2010; Võ, Boettcher, & Draschkow, 2019) or visual search (Goujon, Didierjean, & Thorpe, 2015; Wang & Theeuwes, 2018). As a teaser, let us consider the potential promise of an integrative approach to the study of scene viewing: Visual scenes are complex, but at the same time objects in scenes, much like words in sentences, are not randomly positioned and seem constrained by a "scene grammar" (e.g., objects tend to rest on surfaces rather than float in the air, etc.) which we continuously acquire via exposure to scenes (Võ & Wolfe, 2015; Võ et al., 2019). In other words, the statistical regularities learned in previous experience with our visual environment provide strong predictions regarding what objects could be where and in what proximity to other objects, in a given scene context. Similar to text or spoken language regularities, such scene regularities could be of different grain-sizes and have a hierarchical structure. Indeed, many of the fundamental questions regarding the role SL in reading would have an equivalent parallel in “scene reading”: *What is the full scope of regularities that are present in our visual input* (see for example Graham & Redies, 2010, for a consideration of statistical regularities in art)*? Which of these regularities drive the variance of the ability to efficiently perceive and understand scenes, find and recognize objects embedded within scenes, and learn object categories? Can “hidden” regularities be identified in corpora of our daily visual exposure* (see Clerkin, Hart, Rehg, Yu, & Smith, 2017, for an example of such corpus approach)? *How do the learned visual regularities alleviate the challenges faced by the visual system at different stages of development?*

Integration at the level of neurobiology

Another important consideration regarding the integration of SL into cognitive science is how SL research converges with what is known about basic mechanisms of learning and memory, including their neurobiology and relevant consolidation processes. This is critical for understanding the relationship as well as the possible demarcation lines between “statistical learning” and other theoretical constructs such as “implicit learning” (e.g., Reber, 1967), “procedural learning” (e.g., Squire & Zola, 1996) and “associative (Hebbian) learning” (e.g., Hebb, 1961) (see Bogaerts et al., in press, for discussion).

In the final paper of this volume, Ambrus et al. (2020) draw on the distinction between instructional model-based and incidental model-free learning processes (Daw, Niv, & Dayan, 2005; see also Poldrack & Packard, 2003). They demonstrate that reducing the engagement of the dorsolateral prefrontal cortex (DLPFC) during non-adjacent dependency learning leads to better long-term learning outcomes, and suggest that inhibition of the DLPFC-dependent learning systems impacts the consolidation of acquired non-adjacent regularities. This paper provides an illuminating example how research on the neurobiological mechanisms underlying SL can offer an informative set of neurobiological constraints and predictions for theories of SL across cognition. For example, linking back to language, a recent study that manipulated TMS on the DLPFC like Ambrus et al., demonstrated its facilitatory effect on implicit word-form learning, supporting the hypothesis that a more mature prefrontal cortex may compete with the implicit acquisition of word-forms (Smalle, Panouilleres, Szmalec, & Möttönen, 2017). The findings of Ambrus et al. thus lead to the compelling prediction that less efficient engagement of prefrontal cortex might also improve the quality long-term representations of word-forms.

More generally, the consideration of long-term memory and consolidation processes is critical for studying how real-world regularities are assimilated through experience. Indeed, many domains are characterized by large sets of low-probability regularities and repetitions of those regularities are often separated by delays of hours or days. The process of learning regularities over such longer time windows necessarily involves integration between new learning episodes and stored representations of regularities (see Gómez, 2017, and Frost et al., 2019, for discussions). Although some work on SL has made direct connections with the memory literature (e.g., Christiansen, 2019; Isbilen, McCauley, Kidd, & Christiansen, 2017, 2020; Kim, Seitz, Feenstra, & Shams, 2009; Schapiro, Gregory, Landau, McCloskey, & Turk-Browne, 2014; Schapiro, Kustner, & Turk-Browne, 2012 for exceptions), greater integration of SL and memory research is needed.

Future directions for an integrative approach

This special issue showcases the advantage of integrating work on SL with research in other areas of psychology. The four papers on reading nicely demonstrate what can be gained from such integration—not only in terms of a better understanding of reading but also in revealing the complexity and abundance of different statistical patterns within that domain. This kind of cross-pollination across disciplinary boundaries promises to enrich the study of SL by broadening the focus beyond simple artificial patterns, to the rich and subtle intricacies of real-world cognition (as we saw for reading). It can also enhance the work of researchers who may not think of themselves as doing SL by offering both theoretical and methodological contributions.

The last quarter of a century has seen an explosion of research in SL, much of which has focused on simplified regularities acquired through passive exposure. This has been a productive strategy, allowing researchers to show evidence of SL across different modalities and domains, across different human developmental stages, from infants to older adults, with or without neuroatypicalities, as well as across different species, from rats to songbirds to monkeys (see Krogh et al., 2013; Santolin & Saffran, 2018, for reviews). However, for SL research to move forward, we believe that the field needs to adopt a more nuanced approach that goes beyond passive learning of a few simple distributional patterns and investigates more complex statistical patterns learned by “statistical foragers” who actively engage with interlaced streams of visual, auditory, tactile, and olfactory input from their environment. The good news is that SL research, as reflected by the articles in this special issue, has already begun to move in this direction.

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