Editors' introduction:

Aligning implicit learning and statistical learning: Two approaches, one phenomenon

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Abstract

This editors' introduction provides the background to the special issue. We first outline the rationale for bringing together, in a single volume, leading researchers from two distinct, yet related research strands, implicit learning and statistical learning. The aim of the special issue is to facilitate the development of a shared understanding of research questions and methodologies, to provide a platform for discussing similarities and differences between the two strands and to encourage the formulation of joint research agendas. We then introduce the new contributions solicited for this special issue and provide our perspective on the agenda setting that results from combining these two approaches.

Aligning implicit learning and statistical learning: Two approaches, one phenomenon

The past 20 years have witnessed a particularly strong interest in our ability to rapidly extract information from complex stimulus environments (Armstrong, Frost & Christiansen, 2017; Rebuschat, 2015; Rebuschat & Williams, 2012). This fundamental aspect of cognition is widely believed to underpin many complex behaviors (language acquisition, music perception, social interaction, intuitive decision making, etc.), so it is not surprising that the interest spans practically all disciplines of cognitive science. Research on this topic can be found in two related, yet almost completely distinct research strands, namely "implicit learning" and "statistical learning." Implicit learning research began with the artificial grammar experiments of Arthur Reber and colleagues (e.g., Reber, 1967, 1969; Reber & Millward, 1968) and developed into one of the major paradigms in cognitive psychology (Cleeremans et al., 1998; Perruchet, 2008; Reber, 1993; Shanks, 2005). Statistical learning research was rekindled by the work of Jenny Saffran, Elissa Newport, and Richard Aslin (Saffran, Aslin, & Newport, 1996) and rapidly developed into a particularly productive line of inquiry in developmental psychology (Armstrong et al., 2017; Gómez, 2007; Saffran, 2003).

Both lines of research focus on how we acquire information from the environment. They rely heavily on the use of artificial languages in their experiments (e.g. finite-state or phrase-structure grammars, pseudoword lexicons). In typical statistical learning and implicit learning experiments, participants are initially exposed to stimuli generated by an artificial system and then tested to determine what they have learned. Thus, both approaches share the same ancestry (see Christiansen, 2019), and also share the perspective that artificial languages can tell us something valuable about how we learn natural language (Reber, 2015). Given these and other significant similarities, Perruchet and Pacton (2006) argued that these distinct lines of research actually represent two approaches to a single phenomenon, and Conway and Christiansen (2006) proposed combining the two in name: "implicit statistical learning."[1] Yet, despite frequent acknowledgements that researchers in implicit

[1] In 2016, we organized a symposium on the theme of this topic at the annual meeting of the Cognitive Science Society. Gary Dell, who was a speaker at the event, proposed a further alternative name for the two approaches: "learning".

learning and statistical learning might essentially be investigating the same phenomenon, there is surprisingly little alignment between the two strands.

This special issue of *Topics in Cognitive Science* seeks to address this situation by bringing together leading researchers from the two research communities, implicit learning and statistical learning, in order to (i) develop a shared understanding of research questions and methodologies, (ii) discuss similarities and differences between the two strands, and (iii) formulate joint research agendas. The special issue is based on two events that the editors organized in 2016. The first event was the Fifth Implicit Learning Seminar, a three-day conference that took place at Lancaster University, UK, on June 23-25, 2016.[2] The Implicit Learning Seminar is an international conference series that brings together leading researchers from a variety of disciplines (cognitive psychology, neuroscience, computer science, linguistics) who share an interest in the cognitive and neural bases of implicit learning. For the 2016 edition, we invited abstracts on any topic related to implicit learning or statistical learning, employing one or more of a variety of methods (artificial grammar learning, sequence learning, cross-situational learning, etc.), but particularly encouraged submissions that focused on the role of implicit statistical learning in language.[3] The second event was a symposium at the 2016 meeting of the Cognitive Science Society (CogSci 38, Philadelphia) that focused specifically on the alignment between the two research communities, implicit learning and statistical learning.[4] In both events, our main objective was to establish a dialogue between researchers from the two communities and to provide a platform for discussion. Ten years after the publication of Perruchet and Pacton (2006) and Conway and Christiansen (2006), how much closer were we to combining the two approaches to the same phenomenon? What challenges and opportunities lay ahead?

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[2] Please visit the conference website for more information: https://www.lancaster.ac.uk/implicit-learning-seminar/.

[3] Both research communities refer to language acquisition as a prime example of implicit statistical learning in the real world. The idea of using artificial languages to investigate natural language acquisition was present from the beginning (e.g., Reber, 1967): “I hoped I was creating a mini-environment that could function as a platform to examine natural language learning. It was consciously crafted as a counterbalance to the Chomskyan Nativism which I felt, even then, was deeply flawed.” (Reber, 2015, p.VII)

[4] The abstracts can be accessed here: http://wp.lancs.ac.uk/rebuschat/files/2019/06/Symposium.pdf.

The discussions at both events were positive and lively, and the idea of producing a special issue that reflected these interactions quickly took shape. All authors were involved in presentations at one or both of the events, with the exception of Pierre Perruchet, whose work we kept closely in mind during these events. We have asked our contributors to produce articles that engage with both literatures and that make explicit connections between them whenever possible. We have also requested that articles conclude with a reflection on future directions of research.

In the first article, Morten Christiansen (2019) provides a "tale of two literatures", comparing the implicit learning literature with the one on statistical learning. In his article, Christiansen first traces the history of both literatures before sketching a framework that provides a basis for understanding implicit learning and statistical learning as a unified phenomenon. Christiansen correspondingly advocates the use of the term "implicit statistical learning" (see also Conway & Christiansen, 2006). This article is based on Christiansen's keynote at the Fifth Implicit Learning Seminar; the recorded keynote is available online and complements the article nicely[5]. In the second article, Laura Batterink, Ken Paller and Paul Reber (2019) provide a much-needed review of the neural bases of implicit statistical learning. Batterink and colleagues focus on the neural processes that underpin performance in experimental paradigms employed in implicit learning and statistical learning research. An important insight is that learning across all paradigms is supported by interactions between the declarative and nondeclarative memory systems of the brain. They conclude with a helpful discussion of future directions of research that will facilitate further alignment between the two lines of investigation.

The next four articles in the special issue closely examine the role of implicit statistical learning in the acquisition of a novel language. Inbal Arnon (2019) explores the link between implicit learning, statistical learning and language development. Are the learning processes observed in typical implicit statistical learning experiments likely to play a role in language learning in the wild? If so, how much of language acquisition can be accounted for by distributional learning? In her review, Arnon focuses on two central themes, namely the issue of age invariance (Is learning fully developed

[5] To watch Morten Christiansen's keynote, please follow https://www.youtube.com/watch?v=LH85UFsxjqA&t=17s.

in childhood or does it improve with age?) and the question of variation in learning outcomes (Does implicit statistical learning ability predict outcomes in language learning?). Arnon suggests that the two literatures are studying a fundamentally similar phenomenon and argues in favor of a closer alignment. However, she also argues for caution in our interpretation of current findings as concerns have been raised regarding the reliability of widely-used tasks (e.g., Siegelman, Bogaerts, Christiansen, & Frost, 2017; Siegelman, Bogaerts, & Frost, 2017). In the following article, Pierre Perruchet (2019) makes an important contribution to our understanding of word segmentation by evaluating contrasting theories derived from implicit learning and statistical learning research. The article represents an important follow-up to the seminal review paper published by Perruchet and Pacton (2006). As in the previous paper, the focus is on the formation of elementary cognitive units. Implicit learning and statistical learning research focus on the same phenomena, namely domain-general learning mechanisms acting in incidental, unsupervised learning situations. However, as Perruchet points out, both approaches favor different explanations, focusing either on the selection of chunks or on the computation of transitional probabilities aimed at discovering chunk boundaries. In the article, Perruchet weighs up the evidence for both explanations. He concludes with a comparison of different computational models and with a helpful agenda for future research.

In the fifth article of the special issue, Padraic Monaghan, Christine Schoetensack and Patrick Rebuschat (2019) focus on the implicit statistical learning of words and syntax. They introduce a novel paradigm that combines theoretical and methodological insights from the two traditions of learning – implicit and statistical. Their cross-situational learning task has been used in the statistical learning literature (e.g., Monaghan, Mattock, Davies, & Smith, 2015), while their measures of awareness (verbal reports and subjective measures) have widely been used in implicit learning research (e.g., Dienes & Scott, 2005; Reber, 1967; see Rebuschat, 2013, for review). Monaghan and colleagues show how the two literatures can be conjoined in a single paradigm to explore the phenomenological and learning consequences of statistical structural knowledge. In the sixth article, Michelle Peter and Caroline Rowland (2019) explore the role of implicit statistical learning in syntactic development. It is often accepted that the processes observed in classic implicit learning or statistical learning experiments play an important role in the acquisition of natural language syntax.

As Peter and Rowland point out, however, the results from neither research strand can be used to fully explain how children's syntax becomes adult-like, in part due to important methodological shortcomings. (For example, artificial language studies typically lack semantic information, which is a clear difference from natural language acquisition.) They propose to address this shortcoming by using the structural priming paradigm (Bock, 1986).

The special issue concludes with an article by Arnaud Rey, Laure Minier, Raphaëlle Malassis, Louisa Bogaerts and Joël Fagot (2019). One of the themes that has been widely addressed in both literatures is that of rule learning. While it is widely agreed that the extraction of regularities from the environment is a fundamental facet of cognition, there is still debate about the nature of rule learning. For example, could "rule" learning be reduced to the formation of chunks (e.g., Perruchet, 2019)? Does it require explicit (conscious) strategies, and how is it affected by prior (linguistic) knowledge? Rey and colleagues show that the comparison between human and non-human primates can contribute important insights to this debate. In their paper, they contrast the performance of humans and Guinea baboons (Papio papio) on the same experimental paradigm, a novel online measure of learning. They conclude with a discussion on how the comparative approach can be used to address theoretical questions that will foster the development of a general theory of regularity learning.

The near and far horizons

The future directions offered by the contributors to this special issue indicate that there is substantial benefit from aligning statistical and implicit learning approaches.

The contributions highlight potential advances in understanding *multimodal information integration*. There is growing awareness that language learning is situated, and so multiple information sources can cohere to support learning. Better recognition of the multiple environmental sources of information that support learning, and advances in the interface between learning from different modalities (e.g., Frost et al., 2015; Milne, Wilson & Christiansen, 2018) is changing the way we study statistical learning (Monaghan, 2017), and broadening the remit of structures that are investigated. This expansion of structures aligns the statistical learning field with the implicit learning tradition, but issues remain about the awareness that participants have of the consequent learning, an important theme which is currently understudied (Christiansen, 2019; Monaghan et al., 2019; Perruchet, 2019). Relatedly, there is growing interest in studying *individual differences* in providing refinement in our penetration of the cognitive processes involved in learning, memory, and language. There is now recognition of the insight that individual differences provide to the operation of different cognitive processes in sequence structure learning tasks (e.g., Kidd & Arciuli, 2016; Siegelman, Bogaerts, & Frost, 2017), indicating similarities and distinctions across structures, across modalities, as well as the role of working memory, perceptual abilities, and processing speed in acquisition (Christiansen, 2019; Perruchet, 2019).

Future integration across the two literatures also promises advances in studies of *the role of memory systems in learning*. Distinctions in memory between declarative and procedural memory have typically been associated with implicit and explicit learning, respectively (Ullman, 2004). There are exciting future prospects for drawing together understanding of memory and development and the systems that are involved in language learning in infancy and childhood (Arnon, 2019; Gomez & Edgin, 2016; Kidd & Arciuli, 2016; Peter & Rowland, 2019; Romberg & Saffran, 2010). Relatedly, Batterink et al. (2019) shows how advances in our understanding of methods in neurophysiology, and cognitive neuropsychology, and the memory systems implicated in learning, can inform these fields, and illuminate (sometimes even literally) the shared resources on which tasks in the two literatures draw upon.

Alignment of implicit and statistical research fields also promises advances in understanding and promoting *language learning and instruction*. Traditionally, second language learning has examined the role of implict versus explicit knowledge about language structure, and have tended to fall under the remit of implicit learning (see e.g. the contributions in Andringa & Rebuschat, 2015; Rebuschat, 2015). However, these second language learning studies have traditionally been segregated from studies of first language learning. One issue that is of current interest to the second language learning community, for instance, is the extent to which explicit awareness of different structures is available to the learner, and whether reaching a threshold of performance on statistical learning performance then results in explicit knowledge. Equally, the extent to which explicit knowledge about structure boosts statistical learning is also under scrutiny (e.g., Batterink et al., 2015;

Romberg & Saffran, 2013). The field is close to a systematic framework for this interface between implicit and explicit knowledge and statistical learning, and Monaghan et al. (2019) offer one possible means by which these approaches can be bridged with a single paradigm.

Finally, there has been a rising tide of *comparative studies* of sequence learning that indicate the language-dependence of learning for certain grammatical, or statistical, structures (Beckers, Berwick, Okanoya, & Bolhuis, 2017; Heimbauer, Conway, Christiansen, Beran, & Owren, 2018), and the field is now poised to realise the constraints of learning not only within but across species. Central to this is the use of experimental procedures that generalise across species (see Rey et al., 2019, for examples and discussion) and the testing of structures that link between artificial grammar learning and statistical learning traditions.

Across each of these themes, there is recent and innovative progress in both the implicit and statistical learning literatures. The future research landscape for the integrated approach advocated by the papers in this volume provides for advances in sharing and broadening the range of methodologically rigorous techniques, as well as ensuring deeper theoretical insights into learning behaviour. Alignment will enable these advances to avoid redundancy, draw on a wider research heritage, and harness research discoveries from both traditions.

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