Available online at www.sciencedirect.com

ScienceDirect

Current Opinion in Behavioral Sciences

The prevalence and importance of statistical learning in human cognition and behavior

Brynn E Sherman, Kathryn N Graves and Nicholas B Turk-Browne

Statistical learning, the ability to extract regularities from the environment over time, has become a topic of burgeoning interest. Its influence on behavior, spanning infancy to adulthood, has been demonstrated across a range of tasks, both those labeled as tests of statistical learning and those from other learning domains that predated statistical learning research or that are not typically considered in the context of that literature. Given this pervasive role in human cognition, statistical learning has the potential to reconcile seemingly distinct learning phenomena and may be an under-appreciated but important contributor to a wide range of human behaviors that are studied as unrelated processes, such as episodic memory and spatial navigation.

Address
Department of Psychology, Yale University, 2 Hillhouse Avenue, New Haven, CT 06520, USA

Corresponding author:
Turk-Browne, Nicholas B (nicholas.turk-browne@yale.edu)

Current Opinion in Behavioral Sciences 2020, **32**:15–20

This review comes from a themed issue on **Understanding memory: which level of analysis**

Edited by **Morgan Barense** and **Hugo Spiers**

https://doi.org/10.1016/j.cobeha.2020.01.015

Introduction

Although each day brings new experiences, our world does not present us with a series of novelties. Rather, our experience is highly repetitive and structured. Over the past two decades, a subfield of cognitive science has emerged on how humans acquire this information about the world via *statistical learning*. This research has highlighted that infants, children, adults — and in some cases non-human animals — possess the remarkable ability to detect and represent regularities from the environment in an unsupervised fashion, often without awareness. In this review, we first highlight recent findings demonstrating not only that humans have the capacity for statistical learning, but also that these learned regularities are relevant for behavior throughout the lifespan — from acquiring language to forming predictions about upcoming experiences. We then propose that these mechanisms have behavioral consequences, from facilitating cognitive processing, to shaping representations, to enabling integration over past experiences. Finally, we end by motivating future investigations of statistical learning based on an emerging understanding of its neural foundations, focusing on its reliance on the hippocampus, a brain structure conventionally implicated in episodic memory and spatial navigation.

Mechanisms of statistical learning

Statistical learning is a rapid, efficient means of extracting regularities from the environment. To this end, it has often been studied in the context of development, a period when it is particularly adaptive to quickly learn about the world. However, statistical learning continues to operate and play an important role in cognition throughout the lifespan in adults. Here we review these two bodies of research on statistical learning.

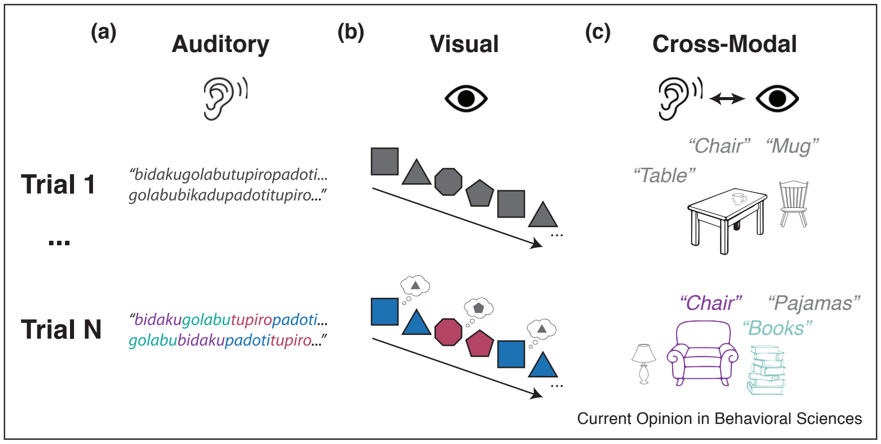
Research in infants

Early work demonstrated that infants can learn auditory regularities after minutes of exposure, suggesting that statistical learning may be a basic building block of language acquisition (see [1]) (Figure 1a). Indeed, a body of subsequent work has demonstrated links between statistical learning and language abilities (see [2]).

These studies demonstrate that statistical learning is important for finding the boundaries between words, and also for mapping those words onto objects and concepts (Figure 1c). The latter has been studied under the banner of cross-situational learning, in which infants learn mappings between heard words and seen objects by tracking their co-occurrences [3], forming hypotheses [4], or a mixture of the two [5].

Advances in head-mounted cameras have provided further insight into how visual input changes over development and how these real-world statistics inform language acquisition [6]. Contrary to the apparent visual clutter of an infant's world, the true distribution of objects in their visual input is right-skewed, such that some objects are encountered with extremely high-frequency [7•]. This skew potentially reduces the ambiguity between auditory words and visual referents: the first nouns learned by

Figure 1



Statistical learning across modalities. **(a)** In the auditory domain, the temporal regularities embedded in a stream of spoken syllables are not immediately apparent on Trial 1. After many exposures (Trial N), the regularities give way to learned boundaries between each triplet of repeated syllables (colors represent learned 'words'). **(b)** In the visual domain, a series of shapes with an underlying pair structure are shown in series. Later in learning (Trial N), but not initially (Trial 1), this learned regularity enables prediction of the second shape within a pair during presentation of the first shape (colors denote learned shape pairs). **(c)** In a cross-modal context, such as learning of object labels, the mapping between auditory labels and visually presented objects is not immediately discernible. However, repeated co-occurrences of certain labels with certain objects enable some mappings to be acquired by Trial N (colors represent learned auditory-visual mappings).

infants are those encountered with high prevalence in egocentric views of daily life [7•].

Early statistical learning work focused on auditory regularities and cross-situational learning studies focused on audiovisual regularities. However, there is also evidence that human infants can learn regularities purely within the visual modality (see [1]) (Figure 1b). Recent work has highlighted the role of visual statistical learning in action processing [8], potentially helping an infant learn how to plan and execute motor behaviors. Beyond action, visual statistical learning may also play a fundamental role in helping infants construct object representations [9], both combining parts into wholes [10] and bridging across space and time [11]. Open questions remain about how statistical learning informs various aspects of perceptual and cognitive development. These are being addressed by new advances in quantifying the natural statistics of early environments [6] and in tracking statistical learning in the developing brain [12]. Future investigations may additionally benefit from online neural measures that track learning in the absence of behavioral demands [13•], a method that thus may be particularly well-suited to studying infant learning.

Research in adults

Statistical learning is pervasive throughout the lifespan, from infants to the elderly [14,15]. Nevertheless there is evidence that statistical learning abilities improve with age for both visual and auditory regularities [16]. Adults are adept at acquiring the underlying structure of experiences across a variety of stimuli from different modalities, such as musical tones [17], faces [18], city names [19••], and physical forces [20•]. Indeed, multiple sets of regularities can be extracted at the same time without interference, such as from hierarchical scenes with temporal regularities at both global and local scales [21].

Although most studies evaluate statistical learning by testing with the exact same stimuli and regularities as during exposure, statistical learning also enables more abstract, generalized knowledge that can transfer flexibly across changes at test. This is true in terms of transfer between space and time, where regularities learned from spatial configurations can be applied to temporal sequences [22]; between modalities, where object familiarity acquired via visual statistical learning facilitates haptic interaction [20•]; and across conceptual levels, where regularities between visual exemplars allow for recognition of category structure (e.g. [19••]).

Despite this flexibility, statistical learning remains largely incidental and automatic. For instance, statistical learning is not modulated by reward magnitude [23] unless participants are explicitly instructed to attend to this information [24]. Moreover, unlike many controlled cognitive processes, statistical learning does not consistently benefit from bilingualism [25,26]. The exact interplay between flexibility and automaticity in adult statistical learning remains an active area of investigation [27].

Behavioral consequences of statistical learning

The adaptive purpose of statistical learning in infancy is readily apparent — for learning about the structure of an unknown world. What are the consequences and benefits for adults? One possibility is that adults are robust statistical learners as a vestige of its importance in development. Alternatively, statistical learning may continue to play an important functional role throughout adulthood. Here, we highlight some of these adaptive benefits.

Facilitating processes: attention and prediction

Statistical learning can facilitate perceptual processing by guiding attention. Studies have shown that attention is automatically drawn to regularities, which can enhance both the detection of targets at the same location and/or with the same features (e.g. [28,29]) and the suppression of distractors [29,30,31]. Attention to regularities facilitates further statistical learning and may serve an adaptive purpose: regularities denote stable aspects of the environment which can be relied upon in the future to generate expectations and scaffold new learning [32]. Indeed, statistical learning has been linked to the ability to make predictions about upcoming stimuli [33,34], which in turn can facilitate (see [35]) or alter [36] perceptual processing.

Shaping representations: compression and associative spreading

By linking features that co-occur in space or time, statistical learning may serve to create conjunctive, object-like representations. Such representational changes have been inferred from behavioral findings that the perception [37,38] and value [39,40] of an object can be influenced irresistibly by its learned associations with other objects and their reward histories. These representational changes also have behavioral consequences for the perception of numerosity: displays with learned regularities are judged to contain fewer objects than displays without regularities [41]. This has been interpreted as evidence that two stimuli paired via statistical learning are represented as fewer than two objects. Although unclear how a distortion of numerosity is adaptive *per se*, it may reveal an important role for statistical learning in compressing inputs from the world to reduce processing load. This has been suggested in the domain of visual working memory, where regularities in the co-occurrence of features can increase memory capacity [42]. Although more work is needed to better understand this kind of compression and its impact on behavior, these findings provide initial evidence that statistical learning may serve a more general purpose in optimizing cognitive resources.

Integrating over experiences: decision-making and memory

Regularities not only prompt the formation of objects and associations, but can also influence decision-making. When reasoning in a complex environment, contingencies aggregated across multiple experiences are more predictive than any individual experience [43]. Acquiring such an internal 'model' of the environment is adaptive for making optimal choices when seeking reward, as in reinforcement learning (e.g. [44,45]). In this context, statistical learning may support the incremental tracking of reward value across experiences [46], including by organizing structured knowledge [47], guiding navigation strategies [48], and building schemas [49].

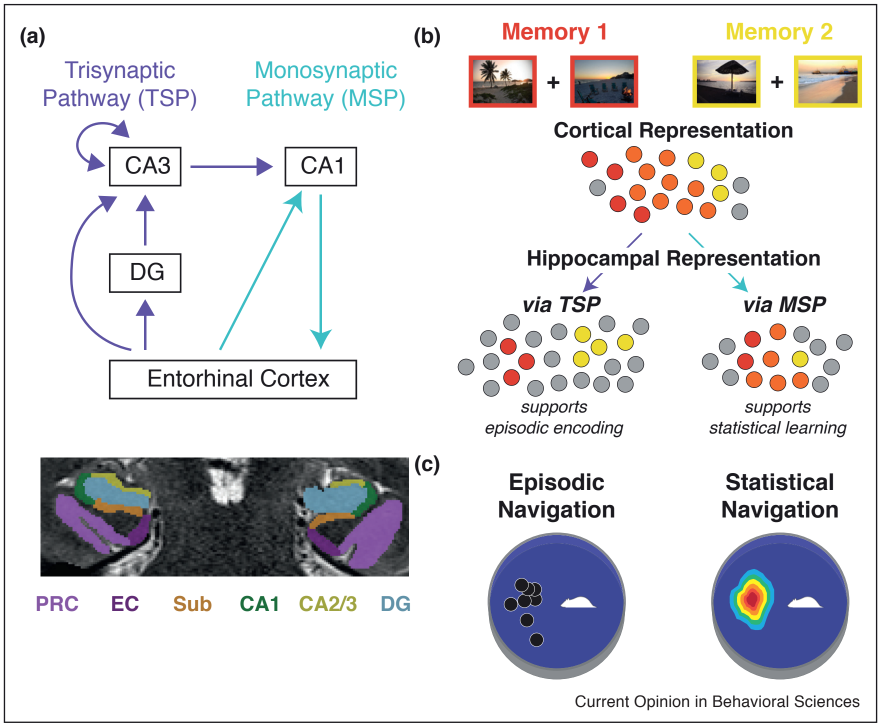
Behavioral implications of statistical learning in the brain

Exploring how statistical learning influences and interacts with other cognitive systems, such as attention, memory, and decision-making, helps to reveal its broad and adaptive role in behavior. However, these studies employ a wide variety of tasks and stimuli, raising the possibility that there are multiple forms of statistical learning. Here we ask whether our understanding of how statistical learning operates in the brain can be used to make novel behavioral predictions and better characterize the full range of influences on behavior. We focus specifically on the hippocampus, as a case study of an important brain region for statistical learning, highlighting implications for future research on episodic memory and spatial navigation.

Each new experience can be encoded distinctly from similar experiences based on its unique moment in space and time. Yet, many of our experiences occur within familiar spatial and temporal contexts, creating a role for learned regularities in seemingly episodic memories. This is supported by findings that memory encoding is sensitive to prediction, a key consequence of statistical learning. In particular, several studies have suggested that prediction errors can affect both old [50] and new [51] memories. Chains of predictions may inform our representations of event structure [52], which in turn can influence both the way we encode unique experiences and the way we navigate space [53].

Critically, episodic memory and spatial navigation are known to rely on the hippocampus, but so are some forms of statistical learning [54,55]. How does the same brain structure simultaneously acquire regularities and encode individual memories? A recent neural network model suggests that the hippocampus may be able to accommodate the computations of both episodic memory and statistical learning via different pathways (Figure 2a) [56••]. Specifically, the trisynaptic pathway (connecting entorhinal cortex to CA1 via dentate gyrus and CA3) has high levels of inhibition and sparse activity patterns, providing the ingredients needed to encode unique episodic traces of related experiences. In contrast, the monosynaptic pathway (a direct recurrent connection between entorhinal cortex and CA1) has lower inhibition resulting in more activity and greater overlap of related experiences, enabling statistical learning.

Figure 2



Statistical learning and episodic memory in the hippocampus. **(a)** The hippocampus contains subfields that support two separate pathways — the trisynaptic pathway (TSP), where input to CA1 from entorhinal cortex (EC) is mediated by dentate gyrus (DG) and CA3, and the monosynaptic pathway (MSP), where EC directly projects to CA1. **(b)** After two similar but distinct trips to the beach, these events (each depicted as a pair of images encountered in sequence during the trip) will be represented in cortex using partially overlapping neural populations. In the hippocampus, however, two kinds of representations would arise. The TSP would encode highly distinct representations of each trip due to sparse coding, minimizing interference and retaining idiosyncratic details in episodic memory. The MSP would encode highly overlapping representations of each trip, supporting the identification of their regularities and statistical learning. **(c)** During navigation, episodic encoding of individual locations may give way to the extraction of underlying spatial patterns, which in turn can guide future navigation to new locations. Although this has previously been shown in rodents only following a long period of consolidation, the architecture of the hippocampus may enable a rapid, online version of this process in humans.

Although this model provides a theoretical solution to how episodic memory and statistical learning occur in tandem in the hippocampus, it is important to note that the two pathways are not independent, most obviously because both terminate in CA1 and output via entorhinal cortex. This anatomical conflict makes the novel behavioral prediction that there will be competition between episodic and statistical processing. For example, two overlapping experiences might be separated into distinct episodic traces if encoded via the trisynaptic pathway, or integrated into related, semanticized traces if encoded via the monosynaptic pathway (Figure 2b). The factors that influence which hippocampal representation wins out remain to be determined, as do the behavioral consequences of this competition.

Related questions exist in spatial navigation, which also depends upon the hippocampus. Just as any experience can be encoded into an episodic memory or used to extract regularities with other experiences, spatial navigation can be driven by episodic details of particular locations (e.g. a specific trip to a new restaurant) or by knowledge of regularities aggregated across multiple bouts of navigation (e.g. a neighborhood that tends to have good food) [48,57•] (Figure 2c). Future work could examine how accounting for these two kinds of spatial learning might help explain complex navigational behavior.

Conclusions and future directions

Throughout this paper, we have explored the pervasive role of statistical learning in human cognition and behavior. We ended with the suggestion, based on a theory of the hippocampus, that one such role of statistical learning may be to influence how and when episodic memories are formed. This approach of generating novel behavioral predictions from an improved neural understanding holds additional promise because statistical learning has been linked to several brain regions beyond the hippocampus. Statistical learning in these regions varies in timescale and content. Within minutes to hours, statistical learning has been observed in inferior frontal and superior temporal cortices for linguistic input [58,59] and in the striatum for motor sequences [60] and reward contingencies [61]. From days to weeks, statistical learning has been linked to cortical consolidation from the hippocampus to medial prefrontal cortex [47,48]. Over months and years, statistical learning shapes much of our generalized, semantic knowledge, from object properties and categories in anterior temporal cortex [62], to spatial, contextual, and conceptual schemas in medial prefrontal cortex [49], to event scripts in posterior medial cortex [63]. This inclusive definition of statistical learning across timescales implicates several brain systems and content domains, suggesting a range of possible impacts of statistical learning on cognition that could be investigated in future studies. The nature of the learning itself within these different systems, specifically which rule(s) govern the plasticity of neural representations [64], also remains to be worked out.

Conflict of interest statement

Nothing declared.

Acknowledgements

This work was supported by funding from the National Institutes of Health (R01 MH069456) to NTB and the National Science Foundation (GRFP) to BES.

References and recommended reading

Papers of particular interest, published within the period of review, have been highlighted as:

- • of special interest
- •• of outstanding interest

1. Saffran JR, Kirkham NZ: **Infant statistical learning**. *Annu Rev Psychol* 2018, **69**:181-203.

2. Arciuli J, Conway CM: **The promise — and challenge — of statistical learning for elucidating atypical language development**. *Curr Direct Psychol Sci* 2018, **27**:492-500.

3. Smith L, Yu C: **Infants rapidly learn word-referent mappings via cross-situational statistics**. *Cognition* 2008, **106**:1558-1568.

4. Aravind A, de Villiers J, Pace A, Valentine H, Golinkoff R, Hirsh-Pasek K, Iglesias A, Wilson MS: **Fast mapping word meanings across trials: young children forget all but their first guess**. *Cognition* 2018, **177**:177-188.

5. Yurovsky D, Frank MC: **An integrative account of constraints on cross-situational learning**. *Cognition* 2015, **145**:53-62.

6. Smith LB, Jayaraman S, Clerkin E, Yu C: **The developing infant creates a curriculum for statistical learning**. *Trends Cogn Sci* 2018, **22**:325-336.

7. • Clerkin EM, Hart E, Rehg JM, Yu C, Smith LB: **Real-world visual statistics and infants' first-learned object names**. *Philos Trans R Soc B: Biol Sci* 2017, **372**:20160055

Analysis of data from infant head-mounted cameras during mealtime events. Different from training sets used for computational models, the distribution of objects in real-world scenes is highly right skewed (i.e. a small proportion of objects are over-represented).

8. Monroy CD, Meyer M, Schröer L, Gerson SA, Hunnius S: **The infant motor system predicts actions based on visual statistical learning**. *NeuroImage* 2019, **185**:947-954.

9. Santolin C, Rosa-Salva O, Vallortigara G, Regolin L: **Unsupervised statistical learning in newly hatched chicks**. *Curr Biol* 2016, **26**: R1218-R1220.

10. Wu R, Gopnik A, Richardson DC, Kirkham NZ: **Infants learn about objects from statistics and people**. *Dev Psychol* 2011, **47**:1220.

11. Johnson SP, Amso D, Slemmer JA: **Development of object concepts in infancy: evidence for early learning in an eye-tracking paradigm**. *Proc Natl Acad Sci U S A* 2003, **100**:10568-10573.

12. Ellis CT, Turk-Browne NB: **Infant fMRI: a model system for cognitive neuroscience**. *Trends Cogn Sci* 2018, **22**:375-387.

13. • Batterink LJ, Paller KA: **Online neural monitoring of statistical learning**. *Cortex* 2017, **90**:31-45

EEG study investigating the neural correlates of auditory statistical learning. Increasing synchrony at the frequency of regularities over the course of exposure can be used as a dynamic, online measure of statistical learning.

14. Campbell KL, Hasher L, Thomas RC: **Hyper-binding: a unique age effect**. *Psychol Sci* 2010, **21**:399-405.

15. Palmer SD, Hutson J, Mattys SL: **Statistical learning for speech segmentation: age-related changes and underlying mechanisms**. *Psychol Aging* 2018, **33**:1035.

16. Shufaniya A, Arnon I: **Statistical learning is not age-invariant during childhood: performance improves with age across modality**. *Cogn Sci* 2018, **42**:3100-3115.

17. Leung Y, Dean RT: **Learning unfamiliar pitch intervals: a novel paradigm for demonstrating the learning of statistical associations between musical pitches**. *PLOS ONE* 2018, **13**: e0203026.

18. Dotsch R, Hassin RR, Todorov A: **Statistical learning shapes face evaluation**. *Nat Hum Behav* 2017, **1**:0001.

19. •• Luo Y, Zhao J: **Statistical learning creates novel object associations via transitive relations**. *Psychol Sci* 2018, **29**:1207-1220

Behavioral evidence for transitive inference and abstraction as a result of statistical learning. Shows that statistical learning can spread through conceptual hierarchies and associative networks.

20. • Lengyel G, Žalalytė G, Pantelides A, Ingram JN, Fiser J, Lengyel M, Wolpert DM: **Unimodal statistical learning produces multimodal object-like representations**. *eLife* 2019, **8**:e43942

Behavioral study of the consequences of unimodal training on multimodal statistical learning. Exposure to objects defined by visual or haptic statistics leads not only to within-modality learning, but also to generalization to the other modality without prior exposure.

21. Jun J, Chong SC: **Visual statistical learning at basic and subordinate category levels in real-world images**. *Attent Percept Psychophys* 2018, **80**:1946-1961.

22. Turk-Browne NB, Scholl BJ: **Flexible visual statistical learning: transfer across space and time**. *J Exp Psychol: Hum Percept Perform* 2009, **35**:195.

23. Rogers LL, Friedman KG, Vickery TJ: **No apparent influence of reward upon visual statistical learning**. *Front Psychol* 2016, **7**:1687.

24. Sisk CA, Remington RW, Jiang YV: **A spatial bias toward highly rewarded locations is associated with awareness**. *J Exp Psychol: Learn Memory Cogn* 2019.

25. Bulgarelli F, Bosch L, Weiss DJ: **Visual statistical learning in monolinguals and bilinguals**. *Front Psychol* 2019, **10**:204.

26. Potter CE, Wang T, Saffran JR: **Second language experience facilitates statistical learning of novel linguistic materials**. *Cogn Sci* 2017, **41**:913-927.

27. Vickery TJ, Park SH, Gupta J, Berryhill ME: **Tasks determine what is learned in visual statistical learning**. *Psychon Bull Rev* 2018, **25**:1847-1854.

28. Zhao J, Luo Y: **Statistical regularities guide the spatial scale of attention**. *Attent Percept Psychophys* 2017, **79**:24-30.

29. van Moorselaar D, Slagter HA: **Learning what is irrelevant or relevant: Expectations facilitate distractor inhibition and target facilitation through distinct neural mechanisms**. *J Neurosci* 2019, **39**:6953-6967.

30. Ferrante O, Patacca A, Di Caro V, Della Libera C, Santandrea E, Chelazzi L: **Altering spatial priority maps via statistical learning of target selection and distractor filtering**. *Cortex* 2018, **102**:67-95.

31. Wang B, van Driel J, Ort E, Theeuwes J: **Anticipatory distractor suppression elicited by statistical regularities in visual search**. *J Cogn Neurosci* 2019:1-14.

32. Kosie JE, Baldwin D: **Attention rapidly reorganizes to naturally occurring structure in a novel activity sequence**. *Cognition* 2019, **182**:31-44.

33. Morgan E, Fogel A, Nair A, Patel AD: **Statistical learning and gestalt-like principles predict melodic expectations**. *Cognition* 2019, **189**:23-34.

34. Kourtzi Z, Welchman AE: **Learning predictive structure without a teacher: decision strategies and brain routes**. *Curr Opin Neurobiol* 2019, **58**:130-134.

35. de Lange FP, Heilbron M, Kok P: **How do expectations shape perception?** *Trends Cogn Sci* 2018, **22**:764-779.

36. Leshinskaya A, Thompson-Schill SL: **From the structure of experience to concepts of structure: how the concept "cause" is attributed to objects and events**. *J Exp Psychol: Gen* 2019, **148**:619.

37. Yu RQ, Zhao J: **Object representations are biased toward each other through statistical learning**. *Visual Cogn* 2018, **26**:253-267.

38. Yu RQ, Zhao J: **Implicit updating of object representation via temporal associations**. *Cognition* 2018, **181**:127-134.

39. Wimmer GE, Shohamy D: **Preference by association: how memory mechanisms in the hippocampus bias decisions**. *Science* 2012, **338**:270-273.

40. Sadacca BF, Wied HM, Lopatina N, Saini GK, Nemirovsky D, Schoenbaum G: **Orbitofrontal neurons signal sensory associations underlying model-based inference in a sensory preconditioning task**. *eLife* 2018, **7**:e30373.

41. Zhao J, Yu RQ: **Statistical regularities reduce perceived numerosity**. *Cognition* 2016, **146**:217-222.

42. Brady TF, Konkle T, Alvarez GA: **Compression in visual working memory: using statistical regularities to form more efficient memory representations**. *J Exp Psychol: Gen* 2009, **138**:487.

43. Daw ND, Niv Y, Dayan P: **Uncertainty-based competition between prefrontal and dorsolateral striatal systems for behavioral control**. *Nat Neurosci* 2005, **8**:1704.

44. Kool W, Gershman SJ, Cushman FA: **Cost-benefit arbitration between multiple reinforcement-learning systems**. *Psychol Sci* 2017, **28**:1321-1333.

45. Momennejad I, Russek EM, Cheong JH, Botvinick MM, Daw ND, Gershman SJ: **The successor representation in human reinforcement learning**. *Nat Hum Behav* 2017, **1**:680.

46. Gershman SJ, Daw ND: **Reinforcement learning and episodic memory in humans and animals: an integrative framework**. *Annu Rev Psychol* 2017, **68**:101-128.

47. Tompary A, Davachi L: **Consolidation promotes the emergence of representational overlap in the hippocampus and medial prefrontal cortex**. *Neuron* 2017, **96**:228-241.

48. Richards BA, Xia F, Santoro A, Husse J, Woodin MA, Josselyn SA, Frankland PW: **Patterns across multiple memories are identified over time**. *Nat Neurosci* 2014, **17**:981.

49. Gilboa A, Marlatte H: **Neurobiology of schemas and schema-mediated memory**. *Trends Cogn Sci* 2017, **21**:618-631.

50. Kim G, Norman KA, Turk-Browne NB: **Neural differentiation of incorrectly predicted memories**. *J Neurosci* 2017, **37**:2022-2031.

51. Greve A, Cooper E, Kaula A, Anderson MC, Henson R: **Does prediction error drive one-shot declarative learning?** *J Memory Lang* 2017, **94**:149-165.

52. Richmond LL, Zacks JM: **Constructing experience: event models from perception to action**. *Trends Cogn Sci* 2017, **21**:962-980.

53. Brunec IK, Moscovitch M, Barense MD: **Boundaries shape cognitive representations of spaces and events**. *Trends Cogn Sci* 2018, **22**:637-650.

54. Schapiro AC, Gregory E, Landau B, McCloskey M, Turk-Browne NB: **The necessity of the medial temporal lobe for statistical learning**. *J Cogn Neurosci* 2014, **26**:1736-1747.

55. Covington NV, Brown-Schmidt S, Duff MC: **The necessity of the hippocampus for statistical learning**. *J Cogn Neurosci* 2018, **30**:680-697.

56. •• Schapiro AC, Turk-Browne NB, Botvinick MM, Norman KA: **Complementary learning systems within the hippocampus: a neural network modelling approach to reconciling episodic memory with statistical learning**. *Philos Trans R Soc B: Biol Sci* 2017, **372**:20160049

Neural network model of the hippocampus that exhibits statistical learning and episodic memory. Trisynaptic pathway supports encoding of individual experiences and monosynaptic pathway extracts regularities across similar experiences. Updates the classic complementary learning systems theory by showing that statistical extraction is not solely contingent on gradual consolidation in cortex.

57. • Chanales AJ, Oza A, Favila SE, Kuhl BA: **Overlap among spatial memories triggers repulsion of hippocampal representations**. *Curr Biol* 2017, **27**:2307-2317

fMRI study of how the brain represents navigational routes. Learning of multiple overlapping routes resulted in the repulsion of their representations in the hippocampus. This pattern separation provides a mechanism to avoid interference between memories, at the cost of being unable to integrate them and extract their regularities.

58. McNealy K, Mazziotta JC, Dapretto M: **Cracking the language code: neural mechanisms underlying speech parsing**. *J Neurosci* 2006, **26**:7629-7639.

59. Karuza EA, Newport EL, Aslin RN, Starling SJ, Tivarus ME, Bavelier D: **The neural correlates of statistical learning in a word segmentation task: an fMRI study**. *Brain Lang* 2013, **127**:46-54.

60. Janacsek K, Shattuck KF, Tagarelli KM, Lum JA, Turkeltaub PE, Ullman MT: **Sequence learning in the human brain: a functional neuroanatomical meta-analysis of serial reaction time studies**. *NeuroImage* 2020, **207**:116387.

61. Goldfarb EV, Chun MM, Phelps EA: **Memory-guided attention: independent contributions of the hippocampus and striatum**. *Neuron* 2016, **89**:317-324.

62. Ralph MAL, Jefferies E, Patterson K, Rogers TT: **The neural and computational bases of semantic cognition**. *Nat Rev Neurosci* 2017, **18**:42.

63. Baldassano C, Hasson U, Norman KA: **Representation of real-world event schemas during narrative perception**. *J Neurosci* 2018, **38**:9689-9699.

64. Ritvo VJ, Turk-Browne NB, Norman KA: **Nonmonotonic plasticity: how memory retrieval drives learning**. *Trends Cogn Sci* 2019, **23**:726-742.