

Brief article

The effect of statistical learning on internal stimulus representations: Predictable items are enhanced even when not predicted



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ABSTRACT

Statistical learning is the automatic and unconscious learning of environmental regularities and is a basic mechanism of learning in a variety of human perceptual and cognitive domains. Previous studies have mainly focused on the associative mechanisms of statistical learning. However, an unexplored question is whether the internal representations of individual stimuli are altered as their associations are learned. Using a temporal statistical learning paradigm, we examine this question across three experiments and find clear evidence that the internal representations of individual stimuli are differentially altered according to their degree of temporal predictability. These findings complement previous accounts of statistical learning and reveal an enriched mechanism of human learning, such that learning to associate items also enhances the representations of certain items relative to others.

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1. Introduction

Statistical learning is the automatic and unconscious learning of environmental regularities (Fiser & Aslin, 2001; Kim, Seitz, Feenstra, & Shams, 2009; Saffran, Aslin, & Newport, 1996; Saffran, Newport, & Aslin, 1996). It is one of the most basic mechanisms of learning in human perceptual and cognitive domains, and it has been studied in relation to language acquisition (Saffran, Aslin, et al., 1996; Saffran, Newport, et al., 1996), attention (Baker, Olson, & Berhmann, 2004; Toro, Sinnett, & Soto-Faraco, 2005; Turk-Browne, Jungé, & Scholl, 2005), development (Kirkham, Slemmer, & Johnson, 2002; Saffran, Aslin et al., 1996; Saffran, Johnson, Aslin, & Newport, 1999), vision (Fiser & Aslin, 2001, 2002, 2005; Kim et al., 2009; Olson & Chun, 2001; Turk-Browne et al., 2005), audition (Saffran

et al., 1999; Seitz, Kim, van Wassenhove, & Shams, 2007), and haptics (Conway & Christiansen, 2005). Research on statistical learning has focused on the mechanisms that drive the learning of associations between groups of stimuli, but it has not explored how the internal representations of the individual stimuli may also be altered as their associations are learned (e.g., O'Brien and Raymond, 2012). In fact there is a divide between the field of perceptual learning (Sagi, 2011), which concentrates on representational changes that occur during slow, explicit, training procedures, and the field of statistical learning, which emphasizes implicit, quickly developing, stimulus–stimulus associations.

The typical approach in statistical learning research is to expose participants to sets of stimuli that have statistically reliable spatial and/or temporal relationships and to test their ability to recognize these statistically associated stimuli. Studies consistently show that human observers are sensitive to these statistically reliable relationships and these groupings are judged to be more familiar than

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novel combinations of stimuli that have been presented an equal number of times as those in the familiar group (Fiser & Aslin, 2001, 2002, 2005; Saffran et al., 1999). But what is it that drives this perception of familiarity? A recent neuro-imaging study found that participants' sense of familiarity for learned sequential pairs was correlated with the fMRI signals related to the second, but not the first, item of the pairs (Turk-Browne, Scholl, Johnson, & Chun, 2010). This suggests that individual group items are processed differently during statistical learning, which may be indicative of differential encoding of their representations. Similarly, research shows that exposure to repeated sequences of shapes leads to faster response times to shapes at the end of a given sequence compared to those at the beginning (Kim et al., 2009; Olson & Chun, 2001; Turk-Browne et al., 2005). While this reduction in reaction times for later group items has been interpreted as a priming effect (i.e., temporal predictability), an unexplored possibility is that of element learning (i.e., improved internal representations of individual predictable items). In other words, it is possible that, in addition to the associative learning mechanisms that operate during statistical learning, there may be perceptual learning mechanisms that shape the representations of individual items according to their degree of temporal predictability.

To directly address the hypothesis that stimulus representations change through statistical learning, we examined participants' responses to individual stimuli both within and outside of learned associative groupings. We utilized a paradigm of temporal statistical learning wherein individual items are grouped into sequences of fixed sequential order, and these groups are in turn presented repeatedly in a randomized order (Fiser & Aslin, 2002; Kim et al., 2009; Turk-Browne et al., 2005). In this paradigm, each item has a particular degree of temporal predictability according to its position within its group. For instance, an item that appears early in a given group is less predictable than an item that appears later in that group. Across three experiments, we tested participants' responses to individual items both within and outside the context of their temporal groupings.

2. General method

In all experiments, participants were exposed to a stream of rapidly presented visual (abstract black-and-white shapes adapted from Fiser & Aslin, 2001) and auditory stimuli (abstract computer-generated sounds from

Kim et al., 2009). Visual stimuli were grouped into six associate pairs (randomly generated for each participant), whereas auditory stimuli were presented in a pseudorandomized order and acted as distractors (except in Experiment 1b where sounds were grouped into pairs and visual stimuli were pseudorandomized and used as distractors). Visual and auditory stimuli were presented synchronously for 300 ms and with an inter-stimulus interval (ISI) of 100 ms (see Fig. 1). Pairs were presented 150 times each in a random sequence (except no pair was repeated in succession).

In each experiment, all test conditions were pseudorandomly interleaved and no feedback was given. For Experiments 1a and 1b, sample sizes were based on previous studies of visual (Kim et al., 2009; Turk-Browne et al., 2005) and auditory (Saffran, Aslin et al., 1996; Saffran et al., 1999) temporal statistical learning, and for Experiment 2 we conducted a power analysis to estimate the sample size needed to detect a small to medium effect size, as expected from a pilot study. See [Supplemental material](#) for additional details about our stimuli and apparatus.

3. Experiments 1a and 1b: Are speeded responses for second items a result of priming?

In our first set of experiments we used a variation of a reaction time test used in previous statistical learning studies (Kim et al., 2009; Olson & Chun, 2001; Turk-Browne et al., 2005). The novelty of our approach is that we measured reaction times for both intact and broken pairs so as to compare responses to the individual items both in the presence and absence of their learned associations.

3.1. Method

Undergraduate students (Experiment 1a: 12 participants, 19–29 years, 5 females; Experiment 1b: 31 participants, 18–28 years, 21 females) passively observed a stream of visual pairs (Experiment 1a; in this case the auditory stream was randomized) or auditory pairs (Experiment 1b; in this case the visual stream was randomized). Participants then completed 120 test trials. In each trial they were first presented with a target stimulus, which they were instructed to detect (via a key press) in a subsequent stream of 10 rapidly presented stimuli (see Fig. 2a). In Experiment 1a each test stream consisted of visual stimuli only, and in Experiment 1b each test stream consisted

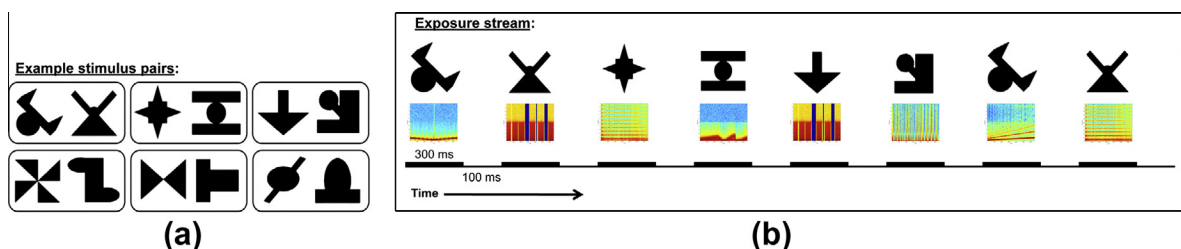


Fig. 1. (a) Example visual stimulus set. (b) Example schematic of the stimulus stream in the exposure phase. The auditory stimuli are represented by their spectrograms.

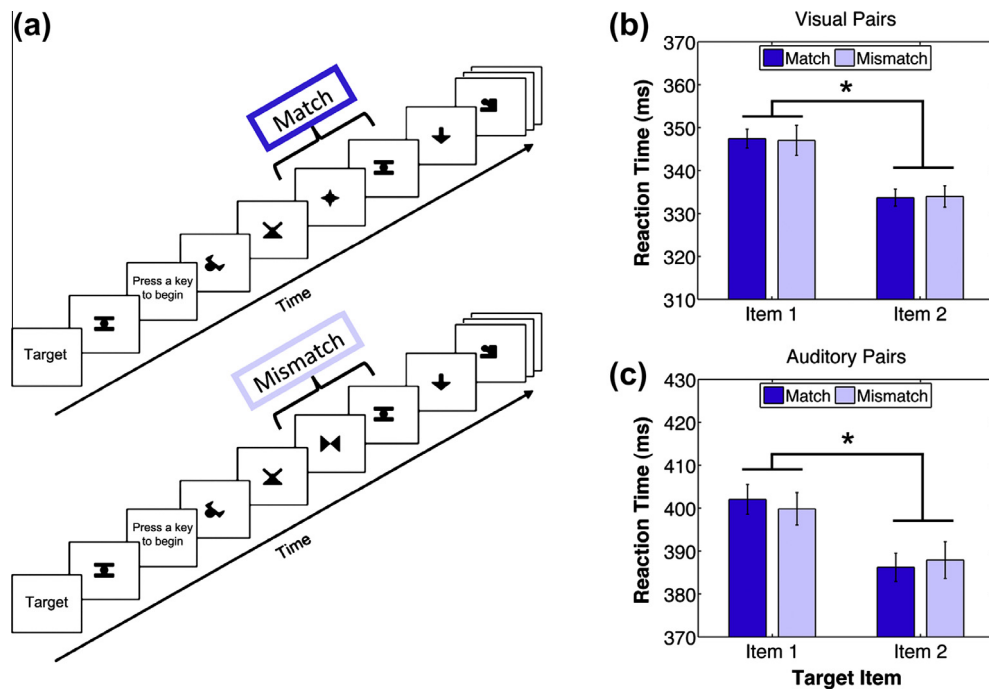


Fig. 2. (a) Example schematic comparing a match and mismatch trial in the reaction time test used in Experiment 1a. An analogous test using auditory stimuli was used in Experiment 1b. (b) Results of Experiment 1a. (c) Results of Experiment 1b. Error bars indicate within-subject standard error of the mean. (*) denotes $p < .05$.

of auditory stimuli only. Each test stream consisted of five of the stimulus pairs presented in a pseudorandomized order with the constraint that the target item was never in the first two or last two positions of the stream. The stimulus durations and ISI were identical to those used in the exposure phase (300 ms and 100 ms, respectively). The target item was either the first or second item of a pair and was followed (item 1 condition) or preceded (item 2 condition) by either its pair-item (match condition) or by another item (mismatch condition) from a pair not included in that trial's test stream. Each stimulus was tested an equal number of times in a pseudorandom order, with the constraint that items from the same pair could not be targets on consecutive trials.

Participants' reaction time data were trimmed of outlier responses by removing reaction times that were 2 or more standard deviations above or below each participant's mean. Additionally, we omitted trials in which participants responded before the onset of the target. These omissions resulted in the removal of approximately 4% of responses overall.

3.2. Results

Replicating prior studies of statistical learning (Kim et al., 2009; Turk-Browne et al., 2005), we found that participants exposed to visual pairs (Experiment 1a; Fig. 2b) responded faster to second items ($M = 334$ ms, $SD = 26.9$) than first items ($M = 347$ ms, $SD = 26.8$), with a 2 (trial type: match vs. mismatch) \times 2 (target item: item 1 vs. item 2) repeated measures ANOVA showing a significant main effect of target item, $F(1, 11) = 10.90$, $p < .01$, $\eta_p^2 = .50$.

To test whether the second item advantage was due to element learning for the second items, response times were compared between match and mismatch trials. We found no effect of trial type, $F(1, 11) = .001$, $p = .97$, nor interaction between trial type and target item, $F(1, 11) = .015$, $p = .91$. To further examine the effect of trial type, paired t -tests (two-tailed) were performed. In the match condition, reaction times were faster for second items ($M = 334$ ms, $SD = 28.3$) than first items ($M = 347$ ms, $SD = 25.9$), $t(11) = 3.60$, $p < .01$, $d = 1.04$. Similarly, in the mismatch condition, reaction times were faster for second items ($M = 334$ ms, $SD = 25.9$) than first items ($M = 347$ ms, $SD = 29.5$), $t(11) = 2.24$, $p < .05$, $d = .65$. These results suggest that the speeded responses for second items may be due to differential item learning rather than priming by the first item.

To test the generality of this effect, we examined statistical learning for auditory pairs (Experiment 1b; Fig. 2c). Here, we observed the same pattern of results, with significantly faster responses to second items ($M = 387$ ms, $SD = 43$) than first items ($M = 401$ ms, $SD = 46.5$) as indicated by a main effect of target item, $F(1, 30) = 6.98$, $p < .05$, $\eta_p^2 = .19$, but no effect of trial type, $F(1, 30) = .004$, $p = .95$, nor interaction between trial type and target item, $F(1, 30) = .402$, $p = .53$. Given the results of Experiment 1a, we ran one-tailed paired t -tests for Experiment 1b. In the match condition, reaction times were faster for second items ($M = 386$ ms, $SD = 46$) than first items ($M = 402$ ms, $SD = 43$), $t(30) = 3.03$, $p < .01$, $d = .54$. Similarly, in the mismatch condition, reaction times were faster for second items ($M = 388$ ms, $SD = 45$) than first items ($M = 400$ ms, $SD = 54$), $t(30) = 1.74$, $p < .05$, $d = .31$.

Together, the results of Experiments 1a and 1b show clear evidence that speeded responses to second items are not simply due to a priming of second items by their associated first items, as speeded responses were found for second items even in the mismatch condition. This indicates that there may be enhanced sensitivity to second items relative to first items as a result of statistical learning, and this hypothesis was examined directly in Experiment 2.

4. Experiment 2: Do second item benefits exist outside of a temporal context?

Experiments 1a and 1b showed a benefit for second items that could not be explained by priming by their associated first items. However, the stimulus sequence in the testing phase was very similar to the exposure phase and it may be that first items yield a non-specific priming to second items. Furthermore, participants were presented with the target item at the start of each trial and, therefore, the second item benefit could have originated either from top-down processes (such as attention) or bottom-up processes (such as representational changes). To address these issues, in Experiment 2 we used a two-interval forced choice shape detection test in which participants were not explicitly informed of the target item at the start of each test trial. As such, participants had to rely entirely on bottom-up sensory information to detect the target stimulus. Importantly, an individual stimulus was tested on each trial; therefore none of the paired associations from the exposure phase were present during the detection test. To control for initial saliency differences between individual items in our stimulus set, we had participants complete the shape detection test both before and after the exposure phase. Thus, our key measure of interest was participants' pre- versus post-exposure change in sensitivity for first and second items of pairs.

4.1. Method

Forty-three participants (ages 18–37; 33 females) underwent an exposure phase identical to Experiment 1a except that a cover task (adapted from Turk-Browne,

Scholl, Chun, & Johnson, 2009) was implemented during the exposure phase to ensure that participants attended to the stimuli during exposure (see [Supplemental material](#) for details).

The shape detection test was completed both before and after the exposure phase (96 trials per test). On each trial, participants indicated which of two intervals contained a shape (other than the fixation cross) by pressing one of two keys. The shape (i.e., the target) was the first or second item of one of the pairs from the exposure phase. In both intervals, a forward and backward mask obscured the stimulus-period (i.e., the period during which the target shape could appear; see [Fig. 3](#)). Each mask was displayed for 100 ms and the stimulus-period was displayed for ~10 ms. The ISI between the stimulus-period and the masking stimuli was ~40 ms (easy-ISI) or ~30 ms (difficult-ISI); the ISI values differed between participants according to a calibration run for each participant. There were an equal number of easy- and difficult-ISI trials. For the post-exposure test, the trials were divided into four blocks, which were interleaved with three brief top-up blocks of exposure stimulus stream. See the [Supplemental material](#) for details about the masking stimuli, calibration, and top-up blocks.

4.2. Results

To examine performance differences between first and second items, we calculated participants' sensitivity (d') as defined in [Stanislaw and Todorov \(1999\)](#). The data were analyzed using a 2 (difficulty: easy vs. difficult) \times 2 (test: pre-test vs. post-test) \times 2 (target item: item 1 vs. item 2) repeated measures ANOVA. As expected, there was a significant main effect of difficulty, where participants showed greater sensitivity in the easy-ISI condition ($M = 2.25$, $SD = 1.53$) compared to the difficult-ISI condition ($M = 1.22$, $SD = 1.34$), $F(1, 42) = 62.34$, $p < .001$, $\eta_p^2 = .60$. There was also a significant main effect of test, such that participants showed greater sensitivity in the post-test ($M = 1.89$, $SD = 1.41$) compared to the pre-test ($M = 1.57$, $SD = 1.40$), $F(1, 42) = 9.09$, $p < .01$, $\eta_p^2 = .21$.

A significant interaction between test and target item indicated enhanced learning for second items compared

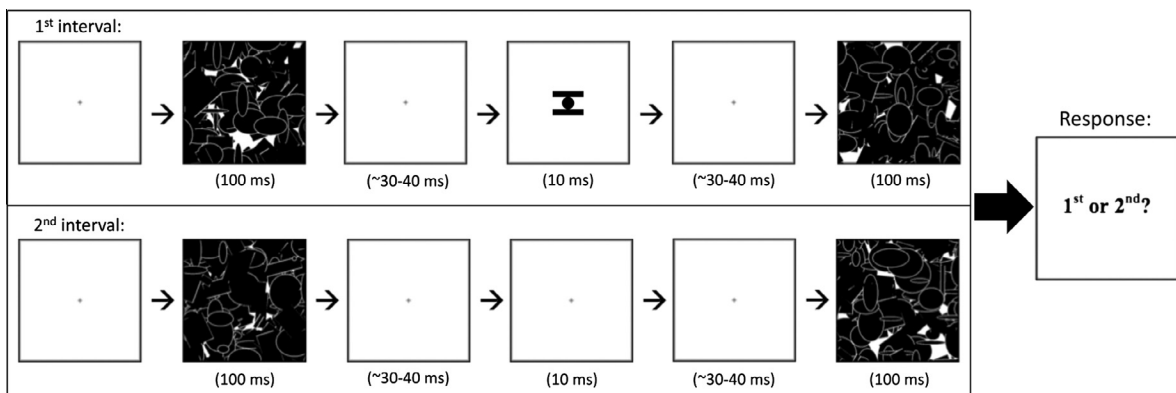


Fig. 3. Example schematic of the two-interval forced choice shape detection test used in Experiment 2.

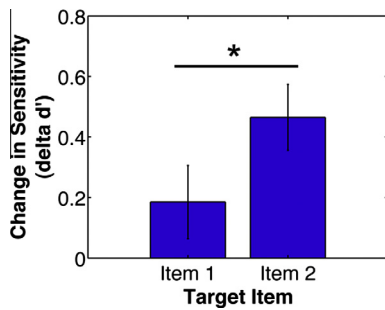


Fig. 4. Change in sensitivity results of Experiment 2, collapsed across the easy- and difficult-ISI conditions. Error bars indicate within-subject standard error of the mean (* denotes $p < .05$).

to first items, $F(1, 42) = 5.19$, $p < .05$, $\eta_p^2 = .11$ (see Fig. 4). When collapsed across difficulty, there was a significant pre-test ($M = 1.46$, $SD = 1.51$) to post-test ($M = 1.93$, $SD = 1.59$) increase in sensitivity for second items, $F(1, 42) = 18.14$, $p < .001$, $\eta_p^2 = .30$, but not first items (pre-test: $M = 1.67$, $SD = 1.36$; post-test: $M = 1.86$, $SD = 1.30$; $p = .13$). As there was a noticeable pre-exposure difference between first and second items (i.e., before any learning could have occurred), to ensure this did not affect our results we performed a follow-up analysis wherein the pre-test performance for first and second items was equated (i.e., by omitting outlier items) and found the same pre- to post-test increase in sensitivity for second items ($p = .001$), but not first items ($p = .20$; see Supplemental material for more details about the follow-up analysis). Additionally, an examination of simple effects revealed that the second item benefit was consistent across both levels of difficulty, such that for both the easy- and difficult-ISI conditions there was a significant pre- to post-test increase in sensitivity for second items ($ps < .01$), but not first items ($ps > .23$). These results confirm that statistical learning results in differential learning for first and second elements in temporally associated pairs.

5. Discussion

The first indication that statistical learning might differentially influence individual stimuli was found in early studies of auditory statistical learning. Specifically, after being exposed to sets of trisyllabic sequences (i.e., non-sense words; Saffran, Newport, et al., 1996) or tritone sequences (Saffran et al., 1999), participants completed a familiarity test in which the patterns of their false alarms indicated a potential difference in their familiarity for elements at the ends of the sequences compared to those at the beginning. Our study extends this finding by showing that statistical learning can differentially influence responses to individual items, and this differential processing exists even when tested outside of their learned groupings and in a context that greatly differs from that of the exposure phase. Specifically, we found that statistical learning can lead to differences in the saliency of predictable (second) compared to less predictable (first) items.

Our results are also consistent with other research showing that statistical learning can result in flexible internal stimulus representations. For instance, Turk-Browne and Scholl (2009) showed that learning of temporal associations transferred to a spatial task and, conversely, that learning spatial associations transferred to a temporal task. Such flexibility suggests that statistical learning may induce representational changes (i.e., perceptual learning) in sensory regions of the brain that are involved in processing the stimuli. Consistent with this, a recent fMRI study on visual statistical learning (Turk-Browne et al., 2009) found that brain regions involved in representing the individual stimuli (i.e., lateral occipital cortex and ventral occipito-temporal cortex) showed a change in neural processing when the stimulus stream contained a statistical structure (i.e., temporally associated stimuli) compared to when it was random. These results are consistent with the hypothesis that sensory areas are sensitive to statistically predictable stimuli and that this may lead to a change in the saliency of these stimuli.

Still, a critical question remains: why should second items of pairs become more salient than first items, rather than the converse? Although the current experiments were not designed to reveal which mechanisms might be at play, there are some plausible mechanisms about which we can speculate. Studies of statistical learning have clearly demonstrated that humans are able to learn statistical regularities in the environment and that this learning arises without instruction or intention. This is in line with the idea, put forth by Biederman and Vessel (2006), that humans are “infovores” who have an innate drive to extract information from the environment. If we assume that the sense of familiarity that accompanies the discovery of a predictable pattern can be intrinsically rewarding, then it may be possible to consider statistical learning within the framework of reinforcement learning. In the context of the current study, it would likely be the case that an intrinsic reward would be associated with the presentation of the second item of a pair (i.e., the time point at which an anticipated pair is confirmed). Indeed, as discussed earlier, in an fMRI study of temporal statistical learning it was found that participants' sense of familiarity for learned pairs versus novel pairs was correlated with the neural processing of second items, but not first items (Turk-Browne et al., 2010).

If the sense of familiarity related to the processing of second items can act as an intrinsic reward, then how might this affect the internal representations of first versus second items? At first glance, one might expect first (i.e., predictive) items to be enhanced relative to second items. For instance, O'Brien and Raymond (2012) found that stimuli that were highly predictive of a monetary win or loss during an initial conditioning phase were subsequently more salient in a recognition task than stimuli that were weakly predictive (or not predictive) of a monetary outcome. However, their participants explicitly learned stimulus-outcome associations, whereas in the current study participants implicitly learned stimulus-stimulus associations, which makes it difficult to draw comparisons between these studies. Instead, there are many aspects of the current study that are more in line with studies of

task-irrelevant perceptual learning wherein stimuli that are presented at behaviorally relevant times are enhanced (Seitz & Watanabe, 2005, 2009); for example, when a particular visual feature (e.g., orientation or motion direction) repeatedly co-occurs with a salient event (e.g., a reward or task-related target), participants subsequently show increased sensitivity to that visual feature in a detection task (Seitz, Kim, & Watanabe, 2009; Seitz & Watanabe, 2003). Seitz and Watanabe (2009) propose that task-irrelevant perceptual learning is gated by reinforcement signals and that stimuli that are concurrent with, and not those that are purely predictive of (Swallow & Jiang, 2011), the release of these signals are those that are best learned. Considering this in the context of the current study, it is possible that second items repeatedly co-occurred with an implicit sense of familiarity (i.e., an intrinsic reward) and that this caused participants to experience enhanced perceptual learning of second items compared to first items.

An attentional mechanism might also explain the current results. Recent research on temporal statistical learning has shown that attention is automatically drawn to statistically reliable stimuli (Zhao, Al-Aidroos, & Turk-Browne, 2013). Thus, in the current paradigm, when first items cue second items during the exposure phase, they may lead to more attentional resources being devoted to the processing of second items, which would in turn enhance the encoding of those items' internal representations. Of course, attentional and reinforcement mechanisms are not mutually exclusive (e.g., Seitz & Watanabe, 2009), and future studies are needed to clarify the mechanisms leading to the asymmetric item-learning effect observed in the current experiments.

An interesting question is the extent to which the current results would extend to, and be impacted by, statistical manipulations other than the bi-directional joint-probabilities employed in our exposure phase. For example, research on reinforcement learning shows that intermediate transitional probabilities can lead to greater activity in the ventral tegmental area (Fiorillo, Tobler, & Schultz, 2003) and to greater learning (Yu & Dayan, 2005). Therefore, it may be hypothesized that a U-shaped effect function could be found peaking at a transitional probability of .75. Additionally, whether backward transitional probabilities (Pelucchi, Hay, & Saffran, 2009; Perruchet & Desauty, 2008) or conditional probabilities (Fiser & Aslin, 2001; Fiser & Aslin, 2002) can impact item-learning remains to be studied.

Overall, our results suggest that temporal statistical learning can result in differences in individual item saliency. Our findings demonstrate that temporal statistical learning is flexible and likely has overlapping mechanisms with perceptual learning.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.cognition.2013.07.003>.

References

- Baker, C. I., Olson, C. R., & Berhmann, M. (2004). Role of attention and perceptual grouping in visual attention. *Psychological Science*, 15, 460–466.
- Biederman, I., & Vessel, E. A. (2006). Perceptual pleasure and the brain: A novel theory explains why the brain craves information and seeks it through the senses. *American Scientist*, 94, 247–253.
- Conway, C. M., & Christiansen, M. H. (2005). Modality-constrained statistical learning of tactile, visual, and auditory sequences. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 31, 24–39.
- Fiorillo, C. D., Tobler, P. N., & Schultz, W. (2003). Discrete coding of reward probability and uncertainty by dopamine neurons. *Science*, 299, 1898–1902.
- Fiser, J., & Aslin, R. N. (2001). Unsupervised statistical learning of higher-order spatial structures from visual scenes. *Psychological Science*, 12, 499–504.
- Fiser, J., & Aslin, R. N. (2002). Statistical learning of higher-order temporal structure from visual shape sequences. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 28, 458–467.
- Fiser, J., & Aslin, R. N. (2005). Encoding multielement scenes: Statistical learning of visual feature hierarchies. *Journal of Experimental Psychology: General*, 134, 521–537.
- Kim, R., Seitz, A., Feenstra, H., & Shams, L. (2009). Testing assumptions of statistical learning: Is it long-term and implicit? *Neuroscience Letters*, 461, 145–149.
- Kirkham, N. Z., Slemmer, J. A., & Johnson, S. P. (2002). Visual statistical learning in infancy: Evidence for a domain general learning mechanism. *Cognition*, 83, B35–B42.
- O'Brien, J. L., & Raymond, J. E. (2012). Learned predictiveness speeds visual processing. *Psychological Science*, 23, 359–363.
- Olson, I. R., & Chun, M. M. (2001). Temporal contextual cuing of visual attention. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 27, 1299–1313.
- Pelucchi, B., Hay, J. F., & Saffran, J. R. (2009). Learning in reverse: Eight-month-old infants track backward transitional probabilities. *Cognition*, 113, 244–247.
- Perruchet, P., & Desauty, S. (2008). A role for backward transitional probabilities in word segmentation? *Memory & Cognition*, 36, 1299–1305.
- Saffran, J. R., Aslin, R. N., & Newport, E. L. (1996). Statistical learning by 8-month-old infants. *Science*, 274, 1926–1928.
- Saffran, J. R., Johnson, E. K., Aslin, R. N., & Newport, E. L. (1999). Statistical learning of tone sequences by human infants and adults. *Cognition*, 70, 27–52.
- Saffran, J. R., Newport, E. L., & Aslin, R. N. (1996). Word segmentation: The role of distributional cues. *Journal of Memory and Language*, 35, 606–621.
- Sagi, D. (2011). Perceptual learning in vision research. *Vision Research*, 51, 1552–1566.
- Seitz, A. R., Kim, R., van Wassenhove, V., & Shams, L. (2007). Simultaneous and independent acquisition of multisensory and unisensory associations. *Perception*, 36, 1445–1453.
- Seitz, A. R., Kim, D., & Watanabe, T. (2009). Rewards evoke learning of unconsciously processed visual stimuli in adult humans. *Neuron*, 61, 700–707.
- Seitz, A. R., & Watanabe, T. (2003). Is subliminal learning really passive? *Nature*, 422, 36.
- Seitz, A. R., & Watanabe, T. (2005). A unified model for perceptual learning. *Trends in Cognitive Science*, 9, 329–334.
- Seitz, A. R., & Watanabe, T. (2009). The phenomenon of task-irrelevant perceptual learning. *Vision Research*, 49, 2604–2610.
- Stanislaw, H., & Todorov, N. (1999). Calculation of signal detection theory measures. *Behavior Research Methods, Instruments, & Computers*, 31, 137–149.
- Swallow, K. M., & Jiang, Y. V. (2011). The role of timing in the attentional boost effect. *Attention, Perception, & Psychophysics*, 73(2), 389–404.
- Toro, J. M., Sennett, S., & Soto-Faraco, S. (2005). Speech segmentation by statistical learning depends on attention. *Cognition*, 97, B25–B34.

- Turk-Browne, N. B., Jungé, J., & Scholl, B. J. (2005). The automaticity of visual statistical learning. *Journal of Experimental Psychology: General*, 134, 552–564.
- Turk-Browne, N. B., & Scholl, B. J. (2009). Flexible visual statistical learning: Transfer across space and time. *Journal of Experimental Psychology: Human Perception and Performance*, 35, 195–202.
- Turk-Browne, N. B., Scholl, B. J., Chun, M. M., & Johnson, M. K. (2009). Neural evidence of statistical learning: Efficient detection of visual regularities without awareness. *Journal of Cognitive Neuroscience*, 21, 1934–1945.
- Turk-Browne, N. B., Scholl, B. J., Johnson, M. K., & Chun, M. M. (2010). Implicit perceptual anticipation triggered by statistical learning. *The Journal of Neuroscience*, 30, 11177–11187.
- Yu, A. J., & Dayan, P. (2005). Uncertainty, neuromodulation, and attention. *Neuron*, 46, 681–692.
- Zhao, J., Al-Aidroos, N., & Turk-Browne, N. B. (2013). Attention is spontaneously biased towards regularities. *Psychological Science*, 24, 667–677.