# MECHANISMS OF RANDOMNESS COGNITION 

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#### Abstract

The environment is inherently noisy, with regularities and randomness. Therefore, the challenge for the cognitive system is to detect signals from noise. This extraction of regularities forms the basis of many learning processes, such as conditioning and language acquisition. However, people often have erroneous beliefs about randomness. One pervasive bias in people's conception of randomness is that they expect random sequences to exhibit greater alternations than typically produced by random devices (i.e., the over-alternation bias). To explain the causes of this bias, in the thesis, I examined the cognitive and neural mechanisms of randomness perception. In six experiments, I found that the over-alternation bias was present regardless of the feature dimensions, sensory modalities, and probing methods (Experiment 1); alternations in a binary sequence were harder to encode and are under-represented compared with repetitions (Experiments 2-5); and hippocampal neurogenesis was a critical neural mechanism for the detection of alternating patterns but not for repeating patterns (Experiment 6). These findings provide new insights on the mechanisms of randomness cognition; specifically, we revealed different mechanisms involved in representing alternating patterns versus repeating patterns.


## Lay Summary

This research aims to explore how the mind extracts different types of patterns in the environment. We examined humans' behaviours and manipulated the neural system of animals to answer this question. The evidence points to a difficulty for the mind to extract alternations compared with repetitions.

## Preface

These studies were conducted at the Behavioral Sustainability Lab and Snyder lab at the University of British Columbia. Experimental design for Chapters 2 and 3 was consulted by Dr. Daniel Osherson (Princeton University). Data collection, and data analysis were conducted by the lead author, Ru Qi Yu, under the supervision of Dr. Jiaying Zhao and in collaboration with Dr. Jason Snyder. Experimental preparation and data collection were helped by the colleagues at the Behavioral Sustainability Lab and the Snyder lab.

Chapters 2 of the thesis has been accepted in the Quarterly Journal of Experimental Psychology (Yu, Gunn, Osherson, \& Zhao, in press), and chapter 3 has recently been accepted in the Journal of Experimental Psychology: Human Perception and Performance (Yu, Osherson, \& Zhao, in press). Chapter 4 is awaiting further data collection and analyses before being written up and submitted to a journal.

All experiments reported here were approved by the UBC Behavioral Research Ethics Board (H13-02684) and UBC Animal Care Committee (A12-0339).

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Dedication

## 1 Introduction

A critical ability for the cognitive system to adapt to the environment is learning.
Learning is the process of acquiring regularities (i.e., signals) that are not random (i.e., noise) in the environment. One of the simplest forms of learning is habituation, where an organism learns to decrease its level of response to a stimulus that repetitively or continuously appears
(Thompson \& Spencer, 1966). The benefit of this form of learning is that if certain stimuli in the environment do not pose any threat, the organism can quickly learn to ignore such stimuli, thereby saving energy. Another prevalent form of learning is associative learning. For example, in classical conditioning, an animal can learn to associate two stimuli that appear reliably and quickly one after another in time, responding to the first conditioned stimulus the same way as they would for the second unconditioned stimulus (Pavlov \& Anrep, 2003). This form of association in classical conditioning forms the basis of anticipation, because the organism learns to respond to a stimulus using its preceding object as a cue, without the need to see the stimulus.

Habituation and associative learning are two prevalent forms of learning, seen from organisms with varying levels of complexity. From organisms with simple neural networks such as C. elegans (Rose \& Rankin, 2001; Rankin et al., 2009) to organisms with more sophisticated neural networks such as humans (Breiter et al., 1996; Davey, 1992), these two forms of learning are ubiquitously observed in neural networks.

What are the neural structures that could support learning? One important structure is the hippocampus. The hippocampus plays a significant role in a many forms of learning. For a simple classical conditioning task involving the association of two reliably occurring stimuli, the hippocampus is critical for learning such association when the two stimuli were separated with a temporal delay (Solomon et al., 1986). The hippocampus is also critical for learning in spatial
tasks that are more complicated to the cognitive system. In a typical Morris water maze task where the rodents had to find an escape platform appearing with other spatial cues in the room, the lesion of the hippocampus will render the animals unable to learn such spatial association (Logue et al., 1997). Furthermore, the hippocampus is also implicated in learning temporal sequences that consist of multiple objects (Fortin et al., 2002).

Memory, which is the maintenance of information over time, is closely related to learning, since information often needs to be extracted through learning to be stored in memory. A widely-known example to attest to the significance of the hippocampus in memory is patient HM. Patient HM suffered from lesions in his Medial-temporal cortical regions, especially the hippocampus (Squire \& Morgan, 1991). The most significant behavioural deficit he demonstrated was retrograde amnesia, where he could not recollect his rather recent experiences before the lesion. It was thought that the hippocampus plays a vital role in the consolidation of experiences into long-term memory (Alvarez \& Squire, 1994). With the hippocampus damaged, the patients' recent experiences cannot enter long-term memory, thus causing retrograde amnesia where the recent memory was lost.

It is important to point out that even for these most fundamental forms of learning and memory, there is a degree of information extraction. That is, learning does not occur simply as the replay of what happened in the environment, but rather, the learning process summarizes the overall likelihood of events in the environment and modifies behaviours accordingly. In the case of habituation, for example, the organism has to learn that the stimulus is present consistently without causing harm, and in the case of classical conditioning, the organism has to learn that the two stimuli reliably follow each other.

For humans, the cognitive system is capable of learning and extracting even more complicated patterns and regularities. For instance, infants can readily extract the reliable cooccurrences of syllables in a temporal sequence (Saffran, Aslin, \& Newport, 1996) and the reliable co-occurrences of shapes in a visual array (Kirkham, Stemmer, \& Johnson, 2002). The cognitive system can also learn the context in which a target is more likely to occur (Chun \& Jiang, 1998), and attention can be directed toward an environment where the target is more likely to occur (Jiang, Swallow, \& Rosenbaum, 2013).

Unlike habituation and conditioning, in these paradigms, the stimuli to be learned often take abstract forms (Turk-Browne et al., 2008), and the learning process is domain-general (Conway \& Christiansen, 2005). The association to be learned often does not involve perfect contingency (Brady, Konkle, \& Alvarez, 2009), unlike those seen in classical conditioning. That means that during the learning process, participants had to learn the strength of the association between certain objects, telling that apart from associations formed randomly between other objects. Such forms of learning that involve distinguishing regularities from randomness are implicit and automatic (Turk-Browne, Junge, \& Scholl, 2005).

The flip side of regularities is randomness, which is the complete lack of structure or predictability. Randomness, in principle, is un-learnable. However, in the real world, people often make mistakes about randomness that lead their decisions astray (Gilovich, Valone, \& Tversky, 1985; Tversky \& Kahneman, 1971). A widespread example is gambling, where the expected outcomes are random. Gamblers are constantly trying to figure out patterns in the theoretically random outcomes, hoping for a better chance of winning. Many decisions depend on the subjective concept of randomness. For example, a stock broker's performance is often evaluated based on whether he/she can reliably outcompete the relatively random fluctuations of
overall market (Bar-Hillel \& Wagenaar, 1991). Randomness is also used to create a fair outcome. For example, coin flips are used to choose the side of the field before a soccer game, and cards need to be thoroughly shuffled before a game of poker.

Despite the widespread application of randomness, people's subjective concept of randomness has not been entirely accurate. During World War II, for example, the city of London went through a series of bombing attacks from the German air force. Anecdotally, it was thought that the locations of the bombing tended to cluster despite post-war analysis of the bombing locations that showed a perfectly random location pattern (Bar-Hillel \& Wagenaar, 1991). Empirically, one classic bias in the subjective concept of randomness is the gambler's fallacy: people think that after seeing a long run of heads, it will be more likely to see tails than heads (Bar-Hillel \& Wagenaar, 1991), even though in a random sequence, the chance of seeing heads or tails is always equal. Another well-known example is the hot-hand fallacy (Gilovich, Valone, \& Tversky, 1985). This is typically observed in basketball, where people think that when a shooter makes a basket, he/she is more likely to make the next basket, even though empirical data suggest that a shooter is equally likely to make the shot after a basket or a miss. These fallacies reveal the nature of the bias in people's perception of randomness. Specifically, people tend to think that longer streaks can not be the consequence of a random process.

Given the prevalence of daily decisions that are based on randomness, there has been a rich body of literature on randomness perception. I will first discuss how people generate a random sequence with multiple unique objects. Because human working memory can only hold a limited number of objects at a given time (Engle, 2002), having participants generate a shuffled and randomized sequence with hundreds of unique objects is infeasible. Most studies on random sequences with multiple unique objects focus a much smaller number of unique objects. In a
study by Treisman \& Faulkner (1987), it was found that when constructing a random sequence with the objects being numbers from 0 to 9 , participants tend to choose the number in the middle more often than the numbers to the two extremes. Due to the large number of possible combinations, other similar studies examined participants' generation of randomness by asking them to come up with a random item among a list of potential objects. However, such methods are much more subjective, and susceptible to biases in verbal knowledge. For example, when participants were asked to generate a random number from 0 to 9 , participants disproportionally choose 7 more often than the other numbers (Kubovy \& Psotka, 1976). The authors postulated that the number 7 was thought to be less random because it was not at the two extremes or the midpoint of the range from 0 to 9 . Additionally, 7 is a prime number, not a multiple of any other numbers. Thus, people would subjectively think of this number as the "most random". For other categories of objects without a clear order such as a number range, the random choice by participants is also heavily affected by semantic knowledge. When participants were asked to randomly pick an object from a category (Rosch, 1978), they often pick the most prototypical one (e.g. chair from furniture).

So far, randomness research on sequences with multiple unique objects has only focused on $0^{\text {th }}$ order relationships. That is, the studies have mostly examined whether the unique objects appeared with even frequencies. Few studies looked at $1^{\text {st }}$ or even higher order relationships in such sequences. That is, how one object transition into the following object in the sequence. This is not surprising given the nature of such sequences. For a sequence with multiple unique objects, there are multiple semantic and experiential factors that can affect how the unique objects can be organized one after another. For example, the way different types of furniture are arranged in a sequence might be completely random for a participant, but the order may perfectly
fit the living room arrangement of another participant, thus fully ordered. The way different colors are arranged might be completely random to one participant, but for synesthetic participants, the colors may be arranged from the saddest to the happiest. Given these constraints, researchers of randomness perception often use binary sequences when investigating how the cognitive system processes randomness beyond $0^{\text {th }}$ order relationships.

In common parlance, the term "random" is applied to sequences of objects that appear sufficiently disorderly or unstructured. For example, the string hthhtthtttht of heads and tails from coin tosses might qualify as random, whereas hhhhhhttttt would not as there are longer repeating streaks. This definition of randomness is based on an existing sequence, or the "product" of a device. Nevertheless, the concept of randomness implies that the results are generated by a process without any rules. A long streak of repeating objects is as likely to be the product of a random process as another sequence with shorter streaks. When assessing whether an existing sequence is the product of a random device, the generating process is unknown. What is typically done in research to quantify randomness in an existing sequence is to analyze certain statistical characteristics of the sequence. Then those certain characteristics would be compared to a sequence that is likely generated from a truly random device. For the $0^{\text {th }}$ order relationship in a binary sequence, the two outcomes would appear with roughly equal frequencies in most cases. For the $1^{\text {st }}$ order relationship in a random sequence, there should be roughly an equal number of alternations in the sequence as repetitions. Alternations are bits that are different from the previous one in the sequence, and repetitions are bits that are the same as the previous one.

The usage of randomness that will be employed in the thesis to generate stimuli applies the term to certain mechanisms for generating events, namely, whose successive outputs are independent and unbiased. A standard example is a device that tosses a fair coin repeatedly
(ignoring other factors that can affect the outcome of the coin toss). Any sequence of heads and tails produced by such a device is qualified as "randomly generated" regardless of its pattern (see Eagle, 2014; Earman, 1986 for an extended discussion between the two approaches). Specifically, in our usage a "random" stimulus (or pattern) is an object that has been produced by a pseudo-random process. Non-random stimuli are defined as productions from a distorted random source.

While the generating process of stimuli is known in the studies, there is no direct evidence of the how participants generated the sequences that they thought would be random. Thus, when participants were asked to generate a random binary sequence, the randomness of their generated sequences is often assessed using the rate of alternations and repetitions in the sequence. The alternation rate for an individual sequence generated by participants may not be a meaningful assessment of the accuracy of their randomness generation, because a random process can generate a sequence with any alternation rate. The alternation rate averaged over multiple sequences generated by participants, on the other hand, can reveal any systematic bias in the human generation of randomness. The reason is that a truly random device over time will generate sequences with roughly equal numbers of alternations and repetitions.

Two well-known biases in people's perception of random binary sequences were the previously discussed Hot-hand fallacy and Gambler's fallacy. Experimental results do support the existence of such fallacies. People tend to think that a random sequence contains more alternations than repetitions. Specifically, when people were asked produce a random binary sequence (Wagenaar, 1972), the produced sequence tends to have more alternations than repetitions, and when people were asked to select the most random sequence, they also end up selecting sequences with more alternations than repetitions (Bar-Hillel \& Wagenaar, 1991).

Additionally, when people were told a sequence is random, they tended to recall shorter runs from the sequence (Olivola \& Oppenheimer, 2008).

Many accounts have been proposed to explain these biases. Some of the earlier accounts focused on the tendency of how people would represent a sequence. As previously discussed for sequences of multiple objects, people tend to think that certain outcomes are more "random" than others. For a long random binary sequence, people tend to think that each local segment carries similar parameters to an average sequence generated by a random device (Kahnemen \& Tversky 1972), i.e. equal numbers of both outcomes. Additionally, as monitoring a long sequence with dozens or hundreds of bits is cognitively challenging, people tend to approach the task of producing a long binary sequence by producing shorter local sequences one after another (Kahnemen \& Frederick, 2002). One of the most critical consequences of this tendency is that attributes that are likely to be present in a local segment of a random sequence, such as long streaks, are altogether avoided in the random sequence produced by people. Such tendency of representing longer sequences by shorter local sequences will result in the abundance of alternations and lack of repetitions in people's generated random binary sequences.

Recent accounts argue that biases of randomness reflect people's limited perceptual experiences with the environment (Hahn \& Warren, 2009; Miller \& Sanjuro, 2015). Both accounts point to the fact that after simulations, a shorter sequence (with around 4 bits) is less likely to exhibit a streak of repetitions. While the accounts are useful in explaining the lack of streaks in participants' generated random binary sequence, it cannot be verified whether the bias in people's subjective concept of randomness is actually based on the experiences that are parallel to the results simulated in these accounts.

Other accounts focus on the effect of information encoding. It was found that at younger ages (when people were children), people would generate a random sequence with more alternations (Kareev 1992). It was hypothesized that younger-aged individuals have shorter memory span, resulting in a greater bias. However, it is difficult to confirm the effect of memory encoding in this study, as many other aspects of cognition have also improved through age.

Other explanations on information encoding have focused on the difficulty to encode random sequences in memory. In the study by Falk \& Konold (1997), it was found that the time it takes for people to accurately encode a binary sequence is highly correlated with how random the sequence is subjectively rated. The most difficult sequences were those with a switch rate between 0.6 to 0.7 . Though the study is not explanatory in that it does not reveal the cause of the over-alternation bias, it does demonstrate the underlying factor of encoding difficulty in the overalternation bias.

There are, however, limitations to the over-alternation bias. For example, people can adequately discriminate both over-alternating sequences and over-repeating sequences against a truly random sequence (Zhao, Hahn, \& Osherson, 2014). Furthermore, people can benefit from an over-alternating sequence to make more effective decisions (Ward, 1973). These studies are important in that they demonstrated that people can tell apart truly random sequences and overalternating sequences, and people can imitate an over-alternating sequence in a task.

This points to two fundamental explanations of the over-alternation bias (Rapaport \& Bedescu, 1992): 1) people have an accurate notion that there should be roughly equal numbers of repetitions and alternations in a sequence, but they misrepresent the number of alternations or repetitions systematically, resulting in the over-alternation bias. 2) people can accurately
represent the number of alternations, but they have a biased notion of randomness, resulting in the over-alternation bias.

The current thesis focuses on three aspects pertaining to the over-alternation bias in the following three research chapters:

1) Is the over-alternation bias domain general? In the paradigm used in previous research, participants usually received the stimuli, or received the feedback of their produced sequences visually. Could the avoidance of streaks be limited to the visual domain, or even be specific to visual features? The first research chapter will focus on examining the over-alternation bias using a variety of paradigms involving stimuli from different domains with different features, and differing probing methods.
2) Is the over-alternation bias driven by perceptual limitations? Accounts such as local representativeness discussed above focus on people's tendency to avoid long streaks when asked to generate random sequences. However, this begs the question of why do participants not avoid a long run of alternations as much as they do for repetitions. Do people conceptually think that alternations are just more random, or are there other limitations in the cognitive system that result in this bias?
3) What is the neural basis that supports the differentiation between the processing of alternations and repetitions?

Before describing the experiments, it is important to clarify the algorithms we used to generate binary sequences. In order to generate binary sequences that contain different levels of alternations and repetitions while maintaining equal probability of the two outcomes, we used an algorithm that deviates from stochastic independence by allowing previous bits to influence the
next one. This algorithm allowed us to manipulate the probability of seeing a repeat versus a switch. Specifically, for each number $p$ in the unit interval (from 0 to 1 ), let $\mathrm{D}(p)$ generate a sequence of bits consisting of zeros and ones as follows:

Sequence generation using the device $D(p)$ : An unbiased coin toss determines the first bit. Suppose that the $n^{\text {th }}$ bit has been constructed (for $n \geqslant 1$ ). Then with probability $p$ the $n+1^{\text {st }}$ bit is set equal to the opposite of the $n^{\text {th }}$ bit; with probability $1-p$ the $n+1^{\text {st }}$ bit is set equal to the $n^{\text {th }}$ bit. Repeat this process to generate a sequence of any desired length.

This algorithm was generated with the framework of Markov chain (Gilks, Richardson, \& Spiegelhalter, 1995). The specific method for generating "random" sequences was first introduced by Zhao, Hahn, and Osherson (2014). It can be seen that $D(.5)$ is a genuinely random device. For $p<.5, D(p)$ tends to repeat itself, resulting in long streaks, whereas for $p>.5, D(p)$ tends to alternate. The expected proportion of each bit is $50 \%$ for all $p \in[0,1]$, although empirically, the output might deviate from $50 \%$ for individual sequences. For any sequence produced by $D(p)$, the expected proportion of alternation, called the "switch rate" of the generating process, is $p$. The expected proportion of repetitions, called the generating "repeat rate", is $1-p$. See Yu et al., (in press) for more discussion of $\mathrm{D}(p)$.

## 2 The consistency in the subjective concept of randomness

### 2.1 Experiment 1

The goal of the current experiment was to assess the extent of over-alternation bias using stimuli in different feature dimensions, sensory domains, and probing methods.

### 2.1.1 Participants

Fifty undergraduate students ( 39 female, mean age $=19.9$ years, $\mathrm{SD}=2.3$ ) from UBC participated for course credit. Participants in all experiments provided informed consent. All experiments reported here have been approved by the UBC Behavioral Research Ethics Board.

### 2.1.2 Apparatus

Participants were seated 50 cm from a computer monitor (refresh rate $=60 \mathrm{~Hz}$ ) and used stereo headphones for auditory stimuli. Stimuli were presented and responses were collected using Matlab Psychophysics Toolbox (http://psychtoolbox.org/).

### 2.1.3 Stimuli and procedure

Each participant completed two tasks: an adjustment task (the first 40 trials) and a production task (the last 24 trials). The adjustment task consisted of 24 temporal trials and 16 spatial trials. There were three types of temporal trials, each containing a binary sequence (Figure 1a). The three types of trials were color trials, shape trials, and auditory trials. In each color trial, the two bits were represented by a green square (RGB values: $3,254,82$ ) and a blue square (RGB values: $6,32,244$ ). In each shape trial, the two bits were a black square and a black circle. The square width and the circle diameter subtended $5.1^{\circ}$. In each auditory trial, the two bits were a high tone (pitch: 392 Hz ) and a low tone (pitch: 262 Hz ). For the temporal trials, one bit was presented at a time for 400 ms and the inter-stimulus interval (ISI) was a blank screen for 200ms. Each type of temporal trials was run eight times, resulting in 24 temporal trials.

Following the temporal trials, participants completed 16 spatial trials, where participants either adjusted a smaller $11 \times 11$ matrix subtending $10^{\circ}$ ( 8 trials), or a larger $81 \times 81$ matrix subtending $9^{\circ}$ (8 trials), to allow for a checkerboard rather than a stripy pattern for fully alternating matrices (Figure 1b). Each matrix was produced by tiling a binary sequence either horizontally or vertically. The order of the direction of tiling (vertical vs. horizontal) was randomized and counterbalanced.

For both the temporal and spatial trials, participants adjusted the temporal sequences or spatial matrices by clicking two buttons: "more repeating" or "less repeating", for as long as they would like, until the sequence/matrix looked maximally random to them. The sequences participants saw were generated with a given switch rate (the chance of seeing an alternation). At the beginning of each trial, the switch rate $p$ was randomly determined. Each time the participant clicked on "more repeating", the switch rate $p$ decreased by 0.025 , and each time the participants clicked on "less repeating", the switch rate increased by $p 0.025$. Accordingly, the sequences generated by $D(p)$ were presented to the participants.

In addition, participants were explicitly told that a maximally random sequence is the one that is most likely to be generated by a random process (e.g., a fair coin). Participants then clicked a separate button to end the trial, and the switch rate in the generating process for the temporal sequences was recorded, but the observed switch rate of the matrices was recorded. This is because there was no way to identify the length of the temporal sequence over which the participant deemed most random.

Participants completed the second production task in the last 24 trials. In each trial, they were first presented with a matrix and then asked to change the color of the cells in the matrix to
make it maximally random. Participants were encouraged to change as many cells in the matrix as they wanted, in order to make the matrix maximally random.

Each matrix was $11 \times 11$ with 121 cells in total, subtending $15^{\circ}$. Each cell could be either black or white, representing the two possible bits. Of the 24 trials, there were three types of matrices which were initially presented to participants (Figure 1d): uniform matrices with all black or white cells (probability of a switch was 0 in the generating process), fully alternating matrices with a sequence (probability of a switch was 1 in the generating process) tiled horizontally or vertically, and fully random matrices with a random sequence (probability of a switch was 0.5 in the generating process) tiled horizontally or vertically.

The trials were presented in a random order. In each trial, participants first viewed the initial matrix, and then clicked on any cell in the matrix to reverse its color. They were told to produce a maximally random matrix, as if all the bits were generated by a truly random process (e.g., a fair coin). They were encouraged to change as many cells as they liked and also take as much time as they needed until the matrix looked fully random. The observed switch rate of the matrix was recorded. For all trials in the experiment, there was no time limit.

### 2.1.4 Results and Discussion

In this experiment, the observed switch rate of the matrix in the adjustment task (the first 40 trials, Figure 1c), and the observed switch rate of the matrix in the production task (the last 24 trials, Figure 1e) were computed in the same way as follows: to compute the switch rate of a matrix, the matrix was transformed into two binary sequences, one by extracting the bits across columns horizontally through the matrix, and another by traversing across rows vertically through the matrix. The switch rates of the two sequences were computed and then averaged. On
average, participants viewed $33.9(\mathrm{SD}=14.1)$ bits in a sequence before making a decision. On average, participants made $14.4(\mathrm{SD}=9.6)$ adjustments before making a decision.


Figure 1. a) In the adjustment task, three types of temporal sequences were presented. In the color sequence, the two bits were green and blue squares. In the shape sequence, the two bits were circles and squares. In the auditory sequence, the two bits were high and low tones. Each sequence started with a random switch rate, and participants adjusted the switch rate until the sequence looked maximally random. b) In the adjustment task, two types of matrices were presented, a small $11 \times 11$ matrix, and a large $81 \times 81$ matrix. Each matrix was generated from a sequence of blue and green squares, tiled vertically or horizontally. Participants adjusted the switch rate of the matrix until it looked maximally random. c) Results of the adjustment task. d) In the production task, three types of the initial $11 \times 11$ matrices were presented to participants. Two examples of each type are shown in the figure. Uniform matrices started with all black or white cells, fully alternating matrices with a fully alternating sequence tiled horizontally or vertically, and fully random matrices with random sequences tiled horizontally or vertically. Participants clicked on the cells in the matrix to change its color, until the matrix appeared maximally random as if the matrix was determined by a random process. (e) In the production task, the
switch rate of participants' produced matrices was presented for each of the three initial matrices. The switch rates were compared against the truly random point 0.5 . (Error bars reflect $\pm 1$ SEM; *p<.05, ** $p<.01$ )

For the temporal trials in the adjustment task, a 3 (three feature dimensions: color, shape, and tone) $\times 2$ (fast vs. slow speed) repeated-measures ANOVA revealed a main effect of feature dimension $\left[F(2,98)=4.74, p=.01, \eta_{p}{ }^{2}=0.09\right]$, but no effect of speed $[F(1,49)=0.05, p=.83$, $\left.\eta_{p}{ }^{2}<0.01\right]$ or interaction $\left[F(2,98)=0.13, p=.88, \eta_{p}{ }^{2}<0.01\right]$. The switch rates were reliably above 0.5 for color $[\mathrm{M}=0.53, \mathrm{SD}=0.08, t(49)=2.33, p=.02, d=0.53]$, shape $[\mathrm{M}=0.56, \mathrm{SD}=0.08$, $t(49)=5.21, p<.001, d=0.74]$, and tone dimensions $[\mathrm{M}=0.56, \mathrm{SD}=0.08, t(49)=5.49, p<.001$, $d=0.78]$, revealing a robust over-alternation bias (Fig.4a). Among the three types of temporal trials, there was a reliable difference $\left[F(2,98)=4.74, p=.01, \eta_{p}{ }^{2}=0.09\right]$; both shape and tone trials were higher than color trials ( $p<.05$ ), but there was no difference between shape and tone trials ( $p=.99$ ).

For the spatial trials in the adjustment task, the switch rates of both the large and small matrices were reliably above 0.5 [for large matrices: $\mathrm{M}=0.52$, $\mathrm{SD}=0.06, t(49)=2.31, p=.03$, $d=0.33$; for small matrices: $\mathrm{M}=0.54, \mathrm{SD}=0.06, t(49)=5.61, p<.001, d=0.79]$. The switch rate of small matrices was reliably higher than those of large matrices $[t(49)=2.19, p=0.03, d=0.38]$.

For the spatial trials in the production task, among the three types of matrices (with the initial matrix being uniform, random, or alternating), there was a reliable difference in the switch rate via a one-way repeated measures ANOVA $\left[F(2,98)=64.59, p<.001, \eta_{p}{ }^{2}=0.57\right]$, with all pairwise comparisons being significant ( $p<.001$ ). This provides evidence for the anchoring effect.

Specifically, when the initial matrix was uniform, the switch rate of the produced matrix was $0.44(\mathrm{SD}=0.12)$, reliably below $0.5[t(49)=3.61, p<.001, d=0.51]$, but when the initial matrix was random, the switch rate of the produced matrix $[\mathrm{M}=0.54, \mathrm{SD}=0.04]$ was reliably above 0.5
$[\mathrm{t}(49)=6.43, \mathrm{p}<0.001, \mathrm{~d}=0.91]$. When the initial matrix was fully alternating, the switch rate of the produced matrix $[\mathrm{M}=0.63, \mathrm{SD}=0.10]$ was reliably above $0.5[t(49)=10.01, p<0.001, d=1.42]$. Additionally, the average switch rate of the produced matrices in this task was not different from that of the temporal task $[t(49)=1.16, p=0.25, d=0.23]$ or spatial task $[t(49)=0.47, p=0.64$, $d=0.07$ ] shown in Fig.4a. This further provides evidence for the consistency of the overalternating bias across different task domains and probing methods.

### 2.2 Chapter Discussion

The goal of the present chapter was to examine consistency in the subjective concept of randomness across different domains. We found a highly stable over-alternation bias across presentation modes (temporal vs. spatial), feature dimensions (color vs. shape), sensory modalities (visual vs. auditory), stimulus size (small vs. large matrices), and probing methods (adjusting the generating process vs. individual bits). These results suggest that the subjective concept of randomness is consistent despite vast stimulus variations. In addition, we found a strong anchoring effect. Specifically, in the temporal trials, the switch rate of the sequences that was deemed as most random was correlated with the starting switch rate of the sequence. Moreover, the switch rate of the produced matrix was lower when the starting matrix was fully uniform than when the starting matrix was fully alternating or random.

The most noteworthy finding of the current chapter was that the over-alternation bias was consistently observed across various stimulus and task domains. This consistency suggests that people's concept of randomness is immune to differences in the stimuli used to embody randomness and in the elicitation methods used to express randomness. People's conception of randomness must therefore have a stable abstract character, applying similarly to distinct physical domains.

## 3 Alternation blindness in the perception of binary sequences

The goal of the present chapter is to examine how people represent alternations and repetitions in a binary sequence. We conducted four experiments using a range of different paradigms to examine how people represent alternations versus repetitions. There was no mention to participants of randomness in any experiment. In Experiment 2, participants viewed a binary sequence and estimated the number of switches or repeats in the sequence, and we measured their estimation accuracy. In Experiment 3, participants briefly viewed a binary sequence and then recalled the sequence bit for bit, and we measured their recall accuracy. In Experiment 4, participants viewed two sequences and judged whether the sequences were the same or different; we measured their sensitivity to change. In Experiment 5, participants searched for a target embedded in a binary sequence; we measured their response time to gauge their attention to switches versus repeats.

### 3.1 Experiment 2

The goal of this experiment was to examine whether there are systematic differences in the estimation of alternations and repetitions in a binary sequence. Specifically, we presented participants binary sequences, either temporally or spatially, and asked them to estimate the number of switches or repeats in each sequence.

### 3.1.1 Participants

Forty-five undergraduate students ( 32 female, mean age $=19.9$ years, $\mathrm{SD}=2.3$ ) from the University of British Columbia (UBC) participated for course credit. Participants in all experiments provided informed consent. All experiments reported here have been approved by the UBC Behavioral Research Ethics Board. We conducted a power analysis in G*Power (Faul, Erdfelder, Lang, \& Buchner, 2007), using an effect size of $\eta_{p}{ }^{2}=0.53$ observed in our prior work
using similar methods and analyses (Zhao \& Yu, 2016). In the previous work, participants estimated the number of dots on the screen for each trial and the data were analyzed using a repeated-measures ANOVA. Based on the power analysis, a minimum of 38 participants would be required to have $95 \%$ power to detect the effect in our paradigm with an alpha level of 0.05 .

### 3.1.2 Apparatus

In this and subsequent experiments, participants were seated 50 cm away from a computer monitor (refresh rate $=60 \mathrm{~Hz}$ ). Stimuli were presented using MATLAB and the Psychophysics Toolbox (http://psychtoolbox.org).

### 3.1.3 Stimuli

In each trial, participants viewed a 30 -bit sequence. Each sequence was binary, containing circles of two different colors: green (RGB value: 02550 ) and blue (RGB value: 00 255). Each circle subtended $0.9^{\circ}$ in diameter (Figure 1a). There were five levels of switch rates in $D(p)$ in generating the sequences, where $p=0.1,0.3,0.5,0.7$, and 0.9 . Correspondingly, there were five levels of repeat rates $(1-p)=0.9,0.7,0.5,0.3$, and 0.1 .

Temporal sequences. For half of the trials, participants viewed a temporal sequence where the 30 circles were presented one after another over time. Each circle was presented at the center of the screen for 100 ms , and the inter-stimulus interval (ISI) was 100 ms with a blank screen (Figure 2a).

Spatial sequences. For the other half of the trials, participants viewed a spatial sequence, where the 30 circles were presented on the screen simultaneously. The circles in the sequence were arranged from left to the right. The space between two adjacent circles in the sequence subtended $0.1^{\circ}$. Each sequence was presented on the screen for 1000 ms (Figure 2a).

### 3.1.4 Procedure

There were 200 trials in total for each participant. In each trial, participants viewed a sequence with one of the five generating switch rates $(0.1,0.3,0.5,0.7$, or 0.9$)$. Each level of switch rate contained 40 trials, among which 20 trials were temporal sequences and 20 trials were spatial sequences. After viewing the 30-bit sequence, participants were asked to estimate either the number of the color switches ( 10 trials), or the number of color repeats ( 10 trials). Specifically, the instruction for estimating color switches was "How many times did a dot have a DIFFERENT color from the previous dot in the sequence?" and the instruction for estimating color repeats was "How many times did a dot have the SAME color as the previous dot in the sequence?". Participants were also told that the range of their estimate was from 0 to 29 ( 29 was the maximum possible number of switches or repeats in the sequence). Participants typed in their estimate after seeing each sequence. In sum, there were three within-subjects factors: the generating switch rate of the sequence (from 0.1 to 0.9 ), the presentation of the sequence (temporal vs. spatial), and the estimation type (switches vs. repeats). The order of the trials was randomized for each participant. There was no mention of randomness in all experiments.

### 3.1.5 Results and Discussion

Before the analyses, we should define three types of switch rates for each sequence.
Estimated switch rate was the derived by dividing the estimated number of switches by 29 (the maximum possible switches in the sequence). Likewise, estimated repeat rate was calculated by dividing the estimated number of repeats by 29 (the maximum possible repeats). For example, if the participant reported that there were 10 switches in the sequence, the estimated switch rate would be $10 / 29=0.34$. If the participant reported that there were 15 repeats in the sequence, the estimated repeat rate would be $15 / 29=0.52$. Observed switch rate was the objective switch rate
in the sequence presented to the participants in each trial. This was calculated by dividing the objective number of switches in the sequence by 29 . Likewise, observed repeat rate was the objective repeat rate (number of repeats divided by 29 ) in the sequence presented in each trial. The generating switch rate was the $p$ in $D(p)$ in the algorithm that generated the sequence. The generating repeat rate was $1-p$. To verify that the presented sequence actually exhibited the generating switch rate or repeat rate, we plotted the overall observed switch rate or repeat rate for each sequence (Figure 2 b to e), which mapped closely to the generating switch rate or repeat rate. The estimated and observed switch rate and repeat rate were plotted in Figure 2 b and d for temporal sequences, and in Figure 2 c and e for spatial sequences.

We computed the signed error between the estimated and the observed switch rate or repeat rate at each of the five generating rates, separately for temporal trials and spatial trials. This signed error (estimated - observed) served as our measure. The goal of the analysis was to examine whether the signed error was different when participants were estimating the number of switches or repeats across the five generating rates. For temporal trials (Figure 2 b and d), a 5 (generating rate: $0.1,0.3,0.5,0.7$, and 0.9$) \times 2$ (estimation type: switches vs. repeats) repeatedmeasures ANOVA revealed a main effect of generating rate $\left[F(4,176)=162.3, p<.001, \eta_{p}{ }^{2}=0.79\right]$ and of estimation type $\left[F(1,44)=49.34, p<.001, \eta_{p}{ }^{2}=0.53\right]$, and a reliable interaction $\left[F(4,176)=10.75, p<.001, \eta_{p}{ }^{2}=0.20\right]$. Post-hoc Tukey HSD analysis showed that across the five generating rates, all pair-wise comparisons were significant [ $p$ 's<.001]. Pair-wise comparisons at each generating rate showed that participants underestimated the number of switches more than repeats at each of the five generating rates [ $p$ 's s<.01]. As revealed by a linear contrast model, the signed error for both repeat and switch estimation linearly decreased in value as the generating rates increased from 0.1 to 0.9 ( $p<.001$ ). To further assess the strength of this linear relationship,
we correlated the signed error with the generating rates for each participant, and found that the error negatively correlated with the generating rate (across participants, mean $r=-0.88$ for repeat estimation and -0.92 for switch estimation), showing that as the number of repeats or switches increased in the sequence, the greater the underestimation was.
a) Task: estimating the number of color switches or repeats

b) Temporal trials: estimation of switches

d) Temporal trials: estimation of repeats


Spatial sequence (30 circles)

c) Spatial trials: estimation of switches

e) Spatial trials: estimation of repeats


Figure 2. Experiment 2. (a) Participants ( $N=45$ ) were presented with temporal sequences or spatial sequences of green and blue circles. Each sequence contained 30 circles. In temporal sequences, the circles were presented one at a time, and in spatial sequences the circles were presented simultaneously on the screen. For each sequence, participants were asked to estimate either the number of circles that had a different color from the previous circle (switch) or the number of circles that had the same color as the previous circle (repeat). (b) The estimated switch rate and the observed switch rate were plotted against the five levels of generating switch rates for temporal trials. (c) The estimated switch rate and the observed switch rate were plotted against the five levels of generating switch rates for spatial trials. (d) The estimated repeat rate and the observed repeat rate were plotted against the five levels of generating repeat rates for temporal trials. (e) The estimated repeat rate and the observed repeat rate were plotted against the five levels of generating repeat rates for spatial trials. (Error bars reflect $\pm 1$ SEM; *p <.05, **p <.01, ***p<.001)

For spatial trials (Figure 2 c and e), the same ANOVA revealed a main effect of generating rate $\left[F(4,176)=107.2, p<.001, \eta_{p}{ }^{2}=0.71\right]$ and of estimation type $[F(1,44)=114.2$, $p<.001, \eta_{p}{ }^{2}=0.72$ ], but no interaction $\left[F(4,176)=0.07, p=.99, \eta_{p}{ }^{2}<0.01\right]$. Post-hoc Tukey HSD analysis showed that across the five generating rates, all pair-wise comparisons were significant [ $p$ 's<.001], except between 0.7 and 0.9 [ $p=.62$ ]. Again, pair-wise comparisons at each generating rate showed that participants underestimated the number of switches more than repeats at each of the five generating rates [ $p \prime \mathrm{~s}<.001$ ]. As revealed by a linear contrast model, the signed error for both repeat and switch estimation linearly decreased in value as the generating rates increased from 0.1 to 0.9 ( $p<.001$ ). Moreover, we found that the signed error negatively correlated with the generating rate across participants (mean $r=-0.82$ for repeat estimation and -0.87 for switch estimation), showing that as the number of repeats or switches increased in the sequence, the greater the underestimation was.

To further explore the signed error, we compared the estimated switch or repeat rate with the observed switch or repeat rate. For temporal trials (Figure 2b), participants over-estimated the switch rate at 0.1 and 0.3 , but under-estimated the switch rate at $0.5,0.7$, and 0.9 . They also over-estimated the repeat rate at 0.1 and 0.3 , but under-estimated the repeat rate at 0.7 and 0.9 (Figure 2d). For spatial trials (Figure 2c), participants over-estimated the switch rate only at 0.1,
and under-estimated the switch rate at $0.3,0.5,0.7$, and 0.9 . They over-estimated the repeat rate at $0.1,0.3$, and 0.5 , but under-estimated the repeat rate at 0.7 and 0.9 (Figure 2e).

The intersection of the estimated curve and the observed curve signals the point where participants made the most accurate estimation. Interestingly, when estimating the number of repeats, participants were the most accurate around 0.5 where the sequences were truly random. For the same random sequence at 0.5 , participants were significantly under-estimating the number of switches. In fact, for people to perceive a 0.5 switch rate, the sequence must contain more than $50 \%$ switches, with a switch rate of around 0.7 (Figure 2 b and c ). This perceptual insensitivity to switches may underlie the conceptual over-alternation bias of randomness. Taken together, these results suggest that alternations in a binary sequence were consistently underrepresented compared with repetitions.

### 3.2 Experiment 3

One explanation for the under-estimation of switches could be due to a failure in working memory. Specifically, people may not be able to hold alternating bits accurately in working memory, mistaking them for repeating bits, thus leading to under-estimation. To examine this possibility, we conducted Experiment 3 where participants were asked to recall each sequence.

### 3.2.1 Participants

Forty-five undergraduate students ( 30 female, mean age=19.6 years, $\mathrm{SD}=1.2$ ) from UBC participated for course credit. We conducted a power analysis in G*Power (Faul et al., 2007), using the effect size from Experiment $2\left(\eta_{p}{ }^{2}=0.53\right)$. We found that a minimum of 38 participants would be required to have $95 \%$ power to detect the effect in our paradigm with an alpha level of 0.05. Thus, we kept the same sample size as in Experiment 2.

### 3.2.2 Stimuli

The stimuli presented to the participants were the same as those in Experiment 2, except for the following three differences: 1) there were 10 circles per sequence instead of 30 , to circumvent a floor effect in the recall task; 2) each circle was slightly larger, subtending $1.4^{\circ}$ in diameter, and the distance between each circle in spatial sequences was $0.2^{\circ}$; and 3) each spatial sequence was presented for 500ms (Figure 3a).

### 3.2.3 Procedure

The procedure was identical to that in Experiment 2, except for one critical difference: after seeing each sequence, participants were asked to recall the sequence they just saw as accurately as they could, by pressing two different keys to produce the green circles (the "G" key) and the blue circles (the "B" key). Participants were instructed to recall the dots in the same order as they appeared. To recall each bit in a temporal sequence, participants pressed one key and the corresponding circle was presented on the screen for 100 ms after each press, and then disappeared. To recall each bit in a spatial sequence, participants pressed one key and the corresponding circle was presented from left to right on the screen after each key press, and remained on the screen.

### 3.2.4 Results and discussion

As shown in Experiment 2, the observed switch rate of the sequences mapped closely onto the generating switch rates. Thus, for all following experiments task performance was plotted against the five generating switch rates.

To assess the accuracy of participants' recalled sequences, we divided the exact matches between the presented sequence and the recalled sequence by 10 . The accuracy was plotted over the five levels of switch rates. For temporal trials (Figure 3b), a one way repeated-measures

ANOVA revealed a significant difference in accuracy across the five switch rates $\left[F(4,176)=75.61, p<.001, \eta_{p}{ }^{2}=0.63\right]$. Post-hoc Tukey HSD analysis showed all pair-wise comparisons were significant except between 0.7 and 0.9 , and 0.5 and 0.9 . As revealed by a linear contrast model, recall accuracy linearly decreased as the switch rate increased from 0.1 to 0.9 ( $p<.001$ ). We also found that across participants recall accuracy negatively correlated with the switch rate (mean $r=-0.86$ ). For spatial trials (Figure 3c), accuracy was different across the switch rates $\left[F(4,176)=111.5, p<.001, \eta_{p}{ }^{2}=0.72\right]$, and post-hoc Tukey HSD analysis showed that all pair-wise comparisons were significant except between 0.7 and 0.9 . As revealed by a linear contrast model, recall accuracy linearly decreased as the switch rate increased from 0.1 to 0.9 ( $p<.001$ ). Across participants recall accuracy negatively correlated with the switch rate (mean $r=$ $-0.86)$. These results demonstrate that as the switch rate of the sequence increased, recall accuracy decreased.

To obtain a more fine-grained comparison between the recall of switches and repeats, we performed two more analyses. From the second bit on in each sequence, we calculated the recall accuracy of each bit depending on whether the bit repeated the previous bit, or switched from the previous bit. We compared the recall accuracy of switching versus repeating bits. For temporal trials (Figure 3d), a 5 (generating rate: $0.1,0.3,0.5,0.7$, and 0.9$) \times 2$ (bit type: repeating vs. switching) repeated-measures ANOVA showed a main effect of generating rate $[F(4,176)=$ 75.61, $\left.p<.001, \eta_{p}{ }^{2}=0.63\right]$ and of bit type $\left[F(1,44)=206.7, p<.001, \eta_{p}{ }^{2}=0.82\right]$, and a reliable interaction $\left[F(4,176)=37.4, p<.001, \eta_{p}^{2}=0.46\right]$. Pair-wise comparisons at each generating rate showed that the recall accuracy of repeating bits was consistently higher than that of switching bits [ $p$ 's<.01]. For spatial trials (Figure 3e), the same ANOVA showed a main effect of generating rate $\left[F(4,176)=111.5, p<.001, \eta_{p}{ }^{2}=0.46\right]$ and of bit type $[F(1,44)=28.84, p<.001$,
$\left.\eta_{p}{ }^{2}=0.40\right]$, and a reliable interaction $\left[F(4,176)=7.18, p<.001, \eta_{p}{ }^{2}=0.14\right]$. Pair-wise comparisons at each generating rate showed that the recall accuracy of repeating bits was higher than that of switching bits $[p$ 's<.001] at switch rates $0.1,0.3$, and 0.5 .
a) Task: recall the sequence

b) Accuracy of all temporal trials

d) Temporal: repeating vs. switching bits

f) Temporal: switch rate of recalled sequences


Spatial sequence (10 circles)

$\xrightarrow[\text { Time }]{$| 500 ms |  recall the dots  <br>  in the sequence  |
| :---: | :---: |
|  until response  |  |$}$

c) Accuracy of all spatial trials

e) Spatial: repeating vs. switching bits

g) Spatial: switch rate of recalled sequences


Figure 3. Experiment 3. (a) Participants $(N=45)$ were presented with 10-bit sequences of green and blue circles in temporal or spatial sequences. Participants were asked to recall the dots in each sequence after seeing the sequence. Accuracy was calculated as the proportion of exact matches in the dots between the presented sequence and participants' recalled sequence, for temporal trials (b) and spatial trials (c). From the second bit on in each sequence, we calculated the recall accuracy of each bit depending on whether the bit repeated the previous bit, or switched from the previous bit. This accuracy was plotted across the five generating switch levels for temporal sequences (d) and spatial sequences (e). For participants' recalled sequences, we also calculated the switch rate of the recalled sequences, plotted with observed switch rate of the presented sequences across the five generating switch levels for temporal trials ( $f$ ) and spatial trials (g). (Error bars reflect $\pm 1$ SEM; *p < .05, **p < .01, ***p<.001)

One problem with the accuracy measure based on exact matches was that it penalizes cases where participants reversed one bit but were nonetheless accurate. For example, take a presented sequence at switch rate $0.9,010101011$, the participant might encode the overall switchiness of the sequence and produced a recall sequence, 101010100. Based on exact matches, the accuracy would be 0 , but the recalled sequence still resembled the presented sequence in its overall switch rate. To circumvent this problem, we conducted another analysis where we calculated the switch rate of the recalled sequence, and compared that to the observed switch rate of the presented sequence (Figure 3 f and g ).

We computed signed error (switch rate of the recalled sequences - observed switch rate) separately for temporal and spatial trials. For temporal trials (Figure 3f), a one way repeatedmeasures ANOVA revealed a significant difference in signed error across the five generating switch rates $\left[F(4,176)=140.7, p<.001, \eta_{p}{ }^{2}=0.76\right]$. Post-hoc Tukey HSD analysis showed all pairwise comparisons were significant except between 0.1 and 0.3 , and 0.1 and 0.5 , suggesting that errors were greater at higher switch rates. For spatial trials (Figure 3g), the same ANOVA revealed a significant difference in signed error across the five switch rates $[F(4,176)=92.54$, $\left.p<.001, \eta_{p}{ }^{2}=0.68\right]$. Post-hoc Tukey HSD analysis showed all pair-wise comparisons were significant except between 0.1 and 0.3 , and 0.1 and 0.5 , suggesting errors were greater at higher switch rates. In addition, comparisons between the switch rate of the recalled sequences and the
observed switch rate showed a reliable difference at every generating rate, except at 0.5 for temporal trials and 0.1 and 0.5 for spatial trials. This analysis suggests that at 0.5 when the sequence contained the same amount of switches and repeats, participants could still recall the sequence with the correct switch rate.

A caveat in this experiment was the balance of the two outcomes in the sequence. At switch rate 0.1 , there was on average only 1 switch in the 10 -bit sequence. As the switch could occur anywhere in the sequence, the sequence could be 0000011111 or 0000000001 (where 0 and 1 here are blue and green circles). The first sequence had an equal frequency of outcomes, but the second was highly unbalanced. Thus, at switch rate 0.1 the frequency of the two outcomes could be a potential confound. To address this issue, we separated sequences at switch rate 0.1 into 11 groups, from sequences with 0 blue circles, 1 blue circle, to the sequences with 10 blue circles. For temporal trials, a repeated-measures ANOVA revealed a significant difference in recall accuracy in exact matches across the 11 levels $[F(10,331)=7.50, p<.001$, $\left.\eta_{p}{ }^{2}=0.18\right]$. Post-hoc Tukey HSD analysis revealed that the accuracy at 50\% (5 blue circles and 5 green circles) was only lower than that at $0 \%, 90 \%$, or $100 \%(0,9$, or 10 blue circles), but not different from the other frequencies. For spatial trials, a repeated-measures ANOVA revealed a significant difference in recall accuracy across the 11 levels $\left[F(10,331)=2.67, p=.004, \eta_{p}{ }^{2}=0.07\right]$. Post-hoc Tukey HSD analysis revealed that the accuracy at 50\% (5 blue circles and 5 green circles) was also lower than that at $0 \%, 90 \%$, or $100 \%(0,9$, or 10 blue circles), but not different from the other frequencies. This means that for highly repeating sequences, recall accuracy for balanced sequences was not that different from unbalanced sequences, except for the extremes. These results revealed three findings: (1) as the sequence became more alternating, recall accuracy diminished; (2) people were better at recalling repeating bits than switching bits in a
sequence; and (3) as the sequence became more alternating, the recalled sequence had fewer switches. The greater recall error in switching bits compared with repeating bits suggests that people are more likely to encode switches as repeats, than to encode repeats as switches. This encoding difference could explain the greater under-estimation of switches compared with repeats in Experiment 2.

### 3.3 Experiment 4

What explains the encoding difficulty of switching bits? One explanation is that switching bits may be less salient than repeating bits, and thus are more difficult to process. To examine salience, in Experiment 4 we used a change detection task where participants detected changes in two binary sequences that were presented one after another.

### 3.3.1 Participants

Forty-five undergraduate students (24 female, mean age=20.6 years, $\mathrm{SD}=1.8$ ) from UBC participated for course credit. We conducted a power analysis in G*Power (Faul et al., 2007), using the effect size from Experiment $3\left(\eta_{p}{ }^{2}=0.63\right)$. We found that a minimum of 22 participants would be required to have $95 \%$ power to detect the effect in our paradigm with an alpha level of 0.05 . Thus, we kept the same sample size for the subsequent experiments as in Experiment 2.

### 3.3.2 Stimuli and procedure

There were 200 trials in total. In each trial, participants were presented with two back-toback sequences of 15 green and blue circles (Figure 4a). The color and size of the circles were identical to those used in Experiment 2. The sequences were generated with one of the five switch rates ( 0.1 to 0.9 ) as before. There were 40 trials per switch rate, 20 of which contained a
change where the color of one randomly selected circle was different between the two sequences, and 20 of which contained no change where the two sequences were the same. In each trial, all circles in the first sequence were presented simultaneously at the center of the screen for 500 ms , with an ISI of 500 ms , followed by the second sequence also presented for 500 ms . Participants had to judge whether the two sequences were the same or different by pressing the " Y " key or the " N " key, respectively. The trials were presented in a random order.

### 3.3.3 Results and discussion

To examine the performance of the change detection task, we calculated A' based on the non-parametric method proposed by Pollack \& Norman (1964). ${ }^{1}$ A' was plotted across the five generating switch rates (Figure 4 b ). There was a reliable difference in A' across the five rates $\left[F(4,176)=40.64, p<.001, \eta_{p}{ }^{2}=0.48\right]$. Post-hoc Tukey HSD analysis showed all pair-wise comparisons were significant except for between 0.5 and 0.9 , or 0.7 and 0.9 . As revealed by a linear contrast model, $\mathrm{A}^{\prime}$ in the change detection task quartically decreased as the switch rate increased from 0.1 to 0.9 ( $p<.001$ ). Across participants, A' negatively correlated with the switch rate (mean $r=-0.72$ ).

In addition, we examined change detection accuracy depending on the local environment where the change occurred. For all trials with a change, we categorized them into three groups: repeats to switches (e.g., 000 to 001,010 , or 100 ), switches to repeats (e.g., 010,001 , or 100 to 000 ), and switches to switches (e.g., 001 to 011 or 101,010 to 110 or 011,100 to 101 or 110). Since we only considered trials where a change occurred, there was no false alarm. Therefore, we used accuracy as the measure here (Figure 4c). Among the three types of changes, there was a reliable difference in accuracy $\left[F(2,88)=55.95, p<.001, \eta_{p}{ }^{2}=0.56\right]$. Post-hoc Tukey HSD

[^0]analysis showed that accuracy in the repeats to switches group was reliably higher than that in the switches to repeats and switches to switches groups [ $p$ 's<.001].
a) Change detection task: are the sequences the same?

Spatial sequences (15 circles)


Figure 4. Experiment 4. (a) Participants $(N=45)$ were presented with two back-to-back sequences. There were 15 blue and green circles in each sequence. In half of the trials, the two sequences differed in the color of one circle, and for the other half the two sequences were the same. Participants were asked to judge if the two sequences were the same or different after seeing the sequences. (b) Each participants' performance was assessed using $A$ ' across the 5 generating switch rates. (c) Trials with changes were categorized into three change groups: 1. repeats to switches (e.g., 000 to 001, 010, or 100), 2. switches to repeats (e.g., 010, 001, or 100 to 000), and 3. switches to switches (e.g., 001 to 011 or 101, 010 to 110 or 011, 100 to 101 or 110). The accuracy in the change detection task was compared across the three types of changes. (Error bars reflect $\pm 1$ SEM; ***p<.001)

As in Experiment 3, we examined whether the frequency of the outcomes influenced performance for sequences at switch rate 0.1 . We separated these highly repeating sequences into 16 groups, from sequences with 0 blue circles, 1 blue circle, to the sequences with 15 blue circles. A repeated-measures ANOVA did not reveal a significant difference in A' across the 16 levels $\left[F(15,313)=1.56, p=.08, \eta_{p}{ }^{2}=0.07\right]$. Thus, at switch rate 0.1 there was no difference in change detection performance due to the frequency of the two outcomes.

These results showed that as the sequence became more alternating, a change in the sequence was harder to detect. This suggests that repetitions were more salient than alternations. Moreover, a change was more salient when a streak was interrupted, than when an alternating pattern became streaky or remained alternating. This differential performance suggests that people may have paid more attention to the streak presented in the first sequence, than to the switches presented in the first sequence.

### 3.4 Experiment 5

Experiment 4 provided some evidence suggesting that alternations were less salient than repetitions. To provide further support for this account, in Experiment 5 we used a visual search task to measure attention to switching vs. repeating sequences. If participants were faster at finding the target in a repeating sequence than in a switching sequence, this would suggest that repetitions draw more attention than alternations. In contrast, if participants were faster at finding target in a switching sequence than a repeating sequence, this would suggest that alternations draw attention more than repetitions.

### 3.4.1 Participants

Forty-five undergraduate students ( 33 female, mean age $=19.6$ years, $\mathrm{SD}=2.1$ ) from UBC participated for course credit.

### 3.4.2 Stimuli and procedure

As in Experiment 4, there were 200 trials, and in each trial, a sequence containing 15 colored circles was presented simultaneously on the screen. One of the randomly selected circles contained a target (a red arrow pointing left "<" or right ">") superimposed on the circle. The target appeared at the same time as the sequence. As before, the sequences were generated with
one of the five switch rates, and there were 40 trials per switch rate. For each trial, participants had to search for the target and to identify the direction at which the arrow was pointing as fast and as accurately as they could (Figure 5a). Half of the trials contained an arrow pointing left, and the other half contained an arrow pointing right. Each sequence was presented for 1500 ms . The trials were presented in a random order.

### 3.4.3 Results and discussion

The accuracy of the target search task was high (mean=97.5\%, $\mathrm{SD}=2 \%$ ). Thus, we only examined the response times of correct trials as our measure of attention (Figure 5b). There was a reliable difference in response time across the five switch rates $[F(4,176)=2.55, p<.05$, $\left.\eta_{p}{ }^{2}=0.05\right]$. Post-hoc Tukey HSD analysis showed a reliable difference in response times only between switch rates 0.1 and 0.5 . As revealed by a linear contrast model, the response time in the visual search task quartically increased as the switch rate increased from 0.1 to 0.9 ( $p<.001$ ). Across participants, the response time positively correlated with the switch rate (mean $r=0.22$ ). This result showed that participants were faster to find the target in sequences with more repetitions than with more switches. This suggests that repeating sequences may draw attention more strongly than switching sequences.
a) Task: target search

b) Target search performance


Figure 5. Experiment 5. (a) Participants were presented with 15-bit sequences of green and blue circles. The target was a small red arrow, pointing either to the left or right, in one of the circles. Participants were asked to report the direction of the arrow as fast and as accurately as they could. (b) Response time of correct trials was plotted over the 5 generating switch rates. (Error bars reflect $\pm 1$ SEM)

As in previous experiments, we examined whether the frequency of the outcomes influenced performance for sequences at switch rate 0.1 . We separated these highly repeating sequences into 16 groups, from sequences with 0 blue circles, 1 blue circle, to the sequences with 15 blue circles. A repeated-measures ANOVA revealed a significant difference in response times across the 16 levels $\left[F(15,592)=2.19, p=.006, \eta_{p}{ }^{2}=0.05\right]$, but post-hoc Tukey HSD analysis did not reveal any difference between individual levels. Thus, at switch rate 0.1 there was no difference in visual search performance due to the frequency of the two outcomes.

### 3.5 Chapter Discussion

The goal of the current chapter was to examine how people represent alternations vs. repetitions in a binary sequence. Across four experiments, we found that the number of alternations was under-estimated more strongly than the number of repetitions (Experiment 2 ). This under-estimation of switches could be explained by constraints in working memory, since recall accuracy diminished as the sequence became more alternating (Experiment 3). The greater encoding difficulty of alternations could be explained by the possibility that alternations are less salient than repetitions. This was supported by the finding that changes were harder to detect as the sequence became more alternating (Experiment 4). Finally, visual targets were slower to be found as the sequence became more alternating, suggesting that alternating sequences draw attention less strongly than repeating sequences (Experiment 5). Overall, these results from four different paradigms (i.e., estimation, working memory, change detection, and visual search tasks) converge to the same finding that people are more blind or insensitive to alternations than to
repetitions, which suggests that alternations are under-represented in memory or perception compared with repetitions.

## 4 Neural basis for learning alternations and repetitions

### 4.1 Experiment 6

The current experiment was conducted in collaboration with Dr. Jason Snyder.
The goal of the current experiment was to examine the role of hippocampal neurogenesis in learning alternating versus repeating patterns. Learning an alternating sequence is computationally distinct from learning a repeating sequence. To learn an alternating pattern, the temporal position of each object in the sequence must be accurately represented. For example, given a sequence of 101010, if the position of the second and third objects are encoded erroneously, the sequence would appear as 110010, breaking the alternating pattern. The precise temporal information does not need to be encoded for learning a repeating pattern, as swapping any two objects in 111111 still results in 111111. If a neural structure is found to be needed for learning alternations but not repetitions, it can be inferred that learning alternations may be neurally distinct, requiring additional neural computations.

The structure of interest, the hippocampus, has unique anatomical features. The hippocampus is a unique neural brain region, in that it constitutes a visually distinct structure in the mammalian brain (Duvernoy, 2005), it has new neurons being generated (Altman \& Das, 1965), and its synaptic strengths can be highly plastic through processes such as Long-term potentiation (Bliss \& Collingridge, 1993). There are recurrent synapses in the CA3 regions of the hippocampus where the excitatory pyramidal cells synapse onto the cells in the same region (Hasselmo et al., 1995). Such recurrent communication within the region could enhance synaptic communications, which would help the ability to extract patterns. Indeed, evidence suggests that pattern separation (the ability to tell subtle differences between objects) is largely dependent on the activities in CA3 (Leutgeb et al., 2007). Recent studies have suggested that pyramidal
neurons in the hippocampus may also specifically represent the temporal information of events (Eichenbaum, 2014).

Specifically, the new neurons generated during adulthood in the hippocampus are found to be important in discriminating fine details in spatial contexts (Clelland et al., 2009). As previously mentioned, learning an alternating pattern, as opposed to a repeating pattern, may require precise temporal encoding of events in the past. Given that the hippocampus plays a critical role in processing temporal information, and that new neurons in the hippocampus are critical in encoding detailed information, we postulated that adult neurogenesis in the hippocampus was critical in extracting temporal details, thus required in learning alternating patterns, but not required for learning repeating patterns.

### 4.1.1 Subjects

23 transgenic "GFAP-TK" Long-Evans rats whose hippocampal neurogenesis could be pharmacologically inhibited (Snyder et al., 2011) were used. They were compared with their wild-type littermates that had normal genotypes. Both groups of rats received treatments of Valganciclovir at postnatal week 6 for 6 weeks, with 50 mg of the drug per treatment, and a treatment every half a week. Subjects were immediately run after the treatment stopped. The transgenic TK rats will have their neurogenesis inhibited after the drug treatment, whereas the wild-type rats will have intact neurogenesis after the treatment.

### 4.1.2 Stimuli and Apparatus

The rats were put into a standard circular Morris water maze (Morris, 1984). The circular pool was divided into four quadrants at the centre in the setup without conspicuous cues to the subjects. There were four possible platform locations, each at the centre of one of the four quadrants. The water was mixed with a white paint so that the white platform was not visually
available to the animals. The water was kept at room temperature during the experiment. The movement of the animals was tracked using Noldus EthoVision (Noldus, Spink, \& Tegelenbosch, 2001).

### 4.1.3 Procedure

All rats, regardless of the genotype were trained in one of the following three water maze patterns. 1) Repeating: the platform appeared in two possible locations; within a day (10 trials), the platform appeared only in one location, across days, the platform alternated between the two possible locations. 2) Alternating: within a day, the platform perfectly alternated between the two locations (ABABAB); the location of the first platform of each day alternated across days 3 ) Random: within and across days, the platform location was determined pseudo-randomly, so that it was equally likely for the platform to repeat or alternate from its previous location. Wild-type rats $(\mathrm{N}=23)$ and TK rats $(\mathrm{N}=26)$ were randomly assigned to one of the three water maze patterns. There were 10 TK rats and 8 wild-type rats trained with the alternating pattern, 9 TK rats and 8 wild-type rats trained with the repeating pattern, and 8 TK rats and 8 wild-type rats trained with platform location randomly determined.

There were four possible location combinations (two diagonal, two straight) used in the experiment. In each location combination, two of the four aforementioned possible platform locations were selected. The assignment of the four location combinations were counterbalanced for WTs and TKs. Each animal was trained with only one combination for 15 days during the experiment.

### 4.1.4 Results and Discussion

Over all the trials, there was no difference in swim speed between TKs and wild-types $[t(47)=0.37, p=.72, d=0.10]$, Therefore, latency to reach the platform was used as the measure of
the animals' task performance. The faster they were able to find the platform, the better they performed in the task.

The current task with two potential platform locations was challenging to the subjects. Until the eleventh day of training, the performance each improved reliably or marginally from the previous day. Thus, we used animals' average performance starting on day 10 as a measure of the stabilized performance after learning.


Figure 6. (a) the latency for animals to reach the platform was compared between TK transgenic rats and intact wild-type rats for each of the three patterns. (b) Within a trial, the average distance from the animal to the correct platform of the trial was compared between TK transgenic rats and intact wild-type rats for each of the three patterns. (c) Within a trial, the average distance from the animal to the other possible yet incorrect platform of the trial was compared between TK transgenic rats and intact wild-type rats for each of the three patterns. (d) Within a trial, a straight line was drawn from the animal's release point to the correct platform. The average distance from the animal to the straight line was compared between TK transgenic rats and intact wild-type rats for each of the three patterns. (Error bars reflect $\pm 1$ SEM; *p<.05)

The performance was compared between the TK transgenic animals and intact wild-type animals for each of the three water maze patterns (Figure 6a). In the repeating pattern, there was
no reliable difference between the TKs and wild-types in the latency to reach the platform $[t(9)=1.04, p=.33, d=1.63]$. Likewise, in the random pattern, there was no reliable difference between the TKs and wild-types in the latency to reach the platform $[t(9)=0.57, p=.58, d=0.75]$. However, in the alternation pattern, the performance of the TKs was reliably slower than the wild-types $[t(13)=2.84, p=.01, d=4.26]$, suggesting that the TKs had a deficit of learning alternating patterns compared with the wild-types.

We used other measures to quantify the movement path of the animals during the task to assess the performance. We first used the average distance between the animal to the correct platform during a given trial to assess performance (Figure 6b). The closer the distance, the better the performance. We found no different between TKs and wild-types in the three platform patterns [ $p$ 's>.58]. Next, we used the average distance between the animal to the possible but incorrect platform during a given trial to assess performance (Figure 6c). The closer the distance, the worse the performance. We found that in the alternating condition, the TKs were reliably closer to the incorrect platform than wild-types $[t(13)=2.34, p=.03, d=3.73]$, but there was no difference in performance in the other two patterns [ $p$ 's>0.28]. Lastly, we used the animal's deviation from an ideal path to assess the performance (Figure 6d). The ideal path is defined as a straight line between the release point of the animal and the correct platform. The deviation is the aggregate distance between the animal and the ideal path during the trial. The shorter the distance, the better the performance. Again, we found that in the alternating condition, the TKs reliably had more aggregate deviation from the ideal path than wild-types $[t(14)=2.65, p=.02$, $d=3.88$ ], but there was no difference in performance in the other two patterns [ $p{ }^{\prime} \mathrm{s}>0.56$ ]. Please note that all the t -tests mentioned here assumed unequal variance of the two samples in the test, resulting the varying degrees of freedom.

### 4.2 Chapter Discussion

Overall, the results showed that the TKs transgenic rats with adult neurogenesis inhibited during training suffered in performance when learning the alternating pattern. They did show this deficit when the platform location was repeating or randomly assigned. This suggested that adult neurogenesis plays a critical role in learning alternating patterns, but not repeating patterns. This result can be interpreted in two ways: 1) Learning repeating patterns and alternating patterns would employ two separate neural mechanisms. This means that while hippocampal neurogenesis is critical in learning alternations, a separate neural mechanism is involved in learning repetitions. Indeed, learning a repeating pattern requires forming a strong association between the location (the platform) and the outcome (escaping from the platform). This association can be forged by the dopamine system (Young, Ahier, Upton, Joseph, \& Gray, 1998). 2) Given the role of neurogenesis in processing fine details, a more parsimonious explanation is that processing alternations is computationally more challenging, thus requiring additional neural resources.

## 5 General Discussion

Over the course of the three research chapters, the results have shown that the concept of randomness has a consistent bias toward over-alternation, regardless of the feature dimensions, sensory domains, or probing methods (Chapter 2). This demonstrated that the over-alternation bias that is prevalent in literature is not a product of sensory avoidance of clusters in a sequence, but an abstract conceptual bias. The source of this conceptual bias can be explained by the underrepresentation of alternations. The results have shown that the number of alternations was consistently under-represented compared with repetitions, alternations in a sequence are more difficult to be encoded correctly, and alternations are less salient and draw less attention (Chapter 3). The difficulty in encoding alternations explained why alternations are under-represented, and further answered the question proposed in the introduction: why are repeating viewed as being to patterned, but not alternations? The last set of results (Chapter 4) probed the neural mechanisms underlying the difficulty in processing alternations compared with repetitions. It was found that neurogenesis is critical for learning alternating patterns, but not for a repeating pattern. Given the role of adult neurogenesis in processing detailed information, one interpretation of the results is that alternations are more neurally challenging to encode and learn.

The over-alternation bias observed in Experiment 1 was less pronounced than that in previous studies on randomness judgments (Bar-Hillel \& Wagenaar, 1991; Falk \& Konold, 1997; Nickerson \& Butler, 2009; Wagenaar, 1972; Zhao et al., 2014). The switch rate of the stimuli that was deemed maximally random in our tasks ranged from 0.52 to 0.63 , whereas in most previous studies the switch rate was above 0.6 . The relatively low switch rate might be driven by the anchoring effect. Since the starting switch rate of the stimuli was around 0.5 for all experiments, this initial anchor may have weakened the over-alternation bias toward true
randomness, lowering the final switch rate of the stimuli that were judged as maximally random. However, it is worth noting that the anchoring effect automatically alters perception without subjective awareness (Tulving \& Schacter, 1990). In our experiments, such bias to anchor to the initial sequence affected the produced sequence, but bias might be largely implicit in our participants which could automatically influence their conscious decision of how random the stimulus looked, although we did not have direct evidence on their awareness.

The findings in Chapter 3 provide evidence for the new account on the over-alternation bias. Specifically, there is a cognitive limitation in the ability to accurately represent alternations as opposed to repetitions in a binary sequence. This means that for people to perceive a 0.5 switch rate, the sequence must contain more than $50 \%$ alternations (in fact around $70 \%$ ). When participants were asked to produce a random sequence, for example, they may discount the number of alternations they have produced in the sequence. If they wish to produce a sequence with roughly an equal number of alternations and repetitions, they would need to produce more alternations for them to perceive that.

Why are alternations under-represented compared with repetitions? We offer two explanations. First, two alternating bits (e.g., 10) may be perceptually more complex than two repeating bits (e.g., 11), and this higher complexity in an alternation could be more difficult to encode. Second, people may implicitly chunk an alternation into a unit (e.g., perceiving 101010 as three chunks of 10 , Zhao \& $\mathrm{Yu}, 2016$ ), but rely on numerosity perception for repetitions (e.g., perceiving 111111 as 1 repeating five times). Both accounts would lead to an underrepresentation of alternations compared with repetitions.

We should note that we were careful not to mention randomness or related concepts at all in Experiments 2-5. This is because when primed with the notion of randomness, people process
the binary sequences differently than if they were not, producing shorter streaks (Olivola \& Oppenheimer, 2008). We wanted to ensure that our experiments were strictly assessing a perceptual phenomenon, not a conceptual one.

The results from Experiments 2 and 3 suggest that participants might encode distinct types of summary statistics at different levels of accuracy from a binary sequence. For example, at switch rate 0.5 , the sequence contained the same amount of alternations and repetitions. Yet, participants severely under-estimated the switch rate but were relatively accurate at estimating the repeat rate (Experiment 2). When recalling the sequence, they were very accurate at producing the same switch rate 0.5 in their produced sequence (Experiment 3). This suggests that participants could implicitly encode a global switch rate of the binary sequence, but when verbally asked, they were less accurate at reporting the number of switches in the sequence.

Chapter 3 reveals a perceptual limitation in the representation of alternations. The experiments in the chapter are important in several ways: first, it provides a new explanation of the over-alternation bias in randomness perception; second, it reveals new insights on the limits in the perception of binary information; and finally, the same finding was replicated in four different paradigms using different measures. The current findings shed light on how people process binary information, which is fundamental to understanding the limits of the cognitive system.

In Chapter 4 we further demonstrated the critical role of hippocampal neurogenesis in learning alternations. Furthermore, the results suggested that learning repetition and alternations may involve differential neural computations, which may result in the differential representation of repetitions and alternations.

It is worth noting that the hippocampus has frequently been implicated in cognitive tasks involving complicated object associations. One of the tasks that is most relevant to Chapter 4 was delay-nonmatch-to-sample task (Deadwyler, Bunn, \& Hampson, 1996), where after a delay, animals had to find a second target that was in the opposite location to the first target. The addition of Chapter 4 further supported the role of the hippocampus in making object associations. However, it should be pointed out that delay-nonmatch-to-sample task is conceptually similar, yet computationally distinct from the task in Chapter 4. In a typical delay-nonmatch-to-sample task, a session only consists of two trials where there were additional cues (e.g. a temporal delay or an additional spatial cue) that segregated different sessions (Winocur, Wojtowicz, Sekeres, Snyder, \& Wang, 2006). What was computationally required to successfully complete a test trial was to know that the second target was different from the first one. In other words, the critical step was to encode "what" happened in the first trial of the session. In the task in Chapter 4, each session consisted of 10 trials evenly distributed in time. The animals had to encode "when" did each trial occur in addition to "what" was the location in each trial in order to successfully learn an alternating pattern and predict the location of the next trial. As discussed in the introduction, if the "when" of each trial was not accurately encoded, the trials animals experienced would not differ from those experienced in the random condition.

This thesis has focused on the difficulty of processing alternations compared with repetitions. It should be clarified that normal individuals do not have difficulties learning alternations. Rather, alternations are harder to encode neurally and perceptually. This difficulty in encoding alternations can lead to more errors in representing alternations, resulting in the under-representation of alternations. Furthermore, as demonstrated by Falk \& Konold (1997), encoding difficulty of a sequence predicts how random the sequence is perceived. The fact that
alternations are harder to encode may lead the subjective experience that alternations are more "random" than repetitions, even though they are both perfectly not random.

In conclusion, this thesis discusses the differential processing of alternations and repetitions. The results show a consist over-alternation bias in the subjective concept of randomness, which can be explained by the under-representation of alternations compared with repetitions. This under-representation was further supported by the differential neural mechanisms involved in learning alternations compared with repetitions.

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