Expectations of clumpy resources influence predictions of sequential events

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Abstract

When predicting the next outcome in a sequence of events, people often appear to expect streaky patterns, such as that sport players can develop a “hot hand”, even if the sequence is actually random. This expectation, referred to as positive recency, can be adaptive in environments characterized by resources that are clustered across space or time (e.g., expecting to find multiple berries on separate bushes). But how strong is this disposition towards positive recency? If people perceive random sequences as streaky, will there be situations in which they forego a payoff because they prefer an unpredictable random environment over an exploitable but alternating pattern? To find out, 238 participants repeatedly chose to bet on the next outcome of one of two sequences of (binary) events, presented next to each other. One sequence displayed events at random while the other sequence was either more streaky (positively autocorrelated) or more alternating (negatively autocorrelated) than chance. The degree of autocorrelation varied in a between-subject design. Most people preferred to predict purely random sequences over those with moderate negative autocorrelation and thus missed the opportunity for above-chance payoff. Positive recency persisted despite extensive feedback and the opportunity to learn more rewarding behavior over time. Further, most participants' choice strategies were best described by a win-stay/lose-shift strategy, adaptive in clumpy or streaky environments. We discuss the implications regarding an evolved human tendency to expect streaky patterns, even if the sequence is actually random.

Keywords

Cognitive bias; Decision-making; Error management theory; Gambler’s fallacy; Hot hand; Patchy environment; Randomness; Streaks

1. Introduction

Many basketball fans believe that players can become "hot", being more likely to score again if they just scored. This common belief persists even though researchers have found no empirical evidence of such systematic streaks (Gilovich, Vallone, & Tversky, 1985). Similarly, gamblers in casinos playing roulette sometimes increase their bets on red numbers after a long string of black numbers has come up (Reichenbach, 1949; Sundali & Croson, 2006). This is despite the fact that most people are aware that roulette wheels are engineered to generate a random sequence of independent events and thereby prevent accurate predictions of the next outcome.

These are just two out of many documented examples where people see regularities and connections among events or sequences that are actually randomly distributed over space and time (Ayton & Fischer, 2004; Falk & Konold, 1997; Wagenaar, 1972). This tendency, sometimes referred to as "apophenia", is something that humans seem particularly prone to. It comes in at least two forms: In the basketball example, people believe that the sequence of events (a streak of baskets) is likely to continue, and hence be *positively* autocorrelated. In the roulette example, people bet on the termination of a run or the end of a sequence of events, thus expecting a *negatively* autocorrelated pattern.

Whether or not a tendency to expect particular patterns is appropriate depends on the actual structure of the environment (Alloy & Tabachnik, 1984; Haselton et al., 2009). For example, in some sports other than basketball, a player’s performance may indeed be streaky, that is positively autocorrelated. In this case betting on the continuation of a streak can be reasonable (Gula & Köppen, 2009). Likewise, for periodic events like the eruption of a geyser or a person becoming hungry around noon every day, betting on an alternating or negatively autocorrelated pattern will increase predictive accuracy (Pinker, 1997). In other cases, however, events may be truly independent with no pattern or regularities in the environment. Examples include the outcome of a roulette wheel mentioned above, flipping a fair coin, or human male-female birth order where the sex of a newborn can hardly be predicted by the sex of earlier siblings (Rodgers & Doughty, 2001).

Past research on pattern perception has found that people may assume positive or negative autocorrelation in many domains of their daily lives (Oskarsson, Boven, McClelland & Hastie, 2009). However, in the majority of studies, random sequences were predominantly perceived as positively autocorrelated, or streaky, rather than negatively autocorrelated—an effect that is sometimes referred to the 'hot hand' belief (Oskarsson et al., 2009; Tyszka, Zielonka, Dacey & Sawicki, 2008; Wilke & Barrett, 2009). The opposite perception of negative autocorrelation, sometimes labeled the gambler’s fallacy, also occurs but seems to be more rare (Bennis, 2004). In the remainder of this paper we will refer to the subjective expectation that a sequence is positively autocorrelated, streaky, or clumpy as *positive recency* and to the subjective expectation that a sequence is negatively autocorrelated, alternating, or dispersed as *negative recency*.

1.1. Reasoning fallacy or adaptive strategy?

In the psychology literature, seeing patterns in environments where none exist has traditionally been regarded as a fallacy or a cognitive error (Gilovich et al., 1985; Tversky & Kahneman, 1974). However, when trying to predict random sequences of independent and equiprobable events, apophenia does not decrease accuracy, because all strategies produce chance-level performance (Bar-Eli, Avugos & Raab, 2006; Rabin, 2002). Therefore, assuming patterns or regularities in a given environment may be a reasonable default strategy: If there is in fact a pattern, expecting that particular pattern can be advantageous by providing an edge in predicting future events, and if there is no pattern, expecting one will not do worse than any other strategy. Expecting the *wrong* pattern when another one exists though can be disastrous. Thus, whether the tendency to assume positive or negative autocorrelation actually qualifies as an adaptive strategy or a fallacy crucially depends on the structure of the environments in which strategies corresponding to these assumptions are used. In nature, patterned resource distributions may be the norm rather than the exception (e.g., distributions of animals, plants and water sources—see Taylor, 1961; Sims et al., 2008) and animal and human foragers appear to adapt their search strategies to these observable statistical regularities in their foraging landscape (Hutchinson, Wilke, & Todd, 2008; Mata, Wilke, & Czienskowski, 2009). We return to this issue in the discussion.

To test the extent to which people exhibit positive or negative recency in an adaptive way requires a setting where these expectations can be distinguished. Experiments where all strategies achieve the same accuracy, as is the case when predicting random sequences, do not provide a strong test of whether cognition is predisposed (i.e., biased) in either direction (McKay & Efferson, 2010). In a more rigorous experimental test, Kareev (1995) had participants repeatedly predict the next event in several binary sequences, using sequences that varied in the degree of autocorrelation in a between-subject design. In that study, participants' prediction accuracy was better for positively autocorrelated (streaky/aggregated) sequences than for negatively autocorrelated (alternating/dispersed) ones. In particular for sequences with small degrees of negative autocorrelation, participants' accuracy did not exceed chance level, suggesting that they did not detect the existing pattern. For the complementary case of small positive autocorrelations, though, participants were able to exploit the available pattern. Thus, positive recency appeared to predominate in this setting.

In line with these results, Wilke and Barrett (2009) hypothesized that positive recency, which they refer to as the hot hand phenomenon, is a cognitive adaptation to the clumped resources that were prevalent in ancestral environments (see also Wilke & Todd, 2010). In two computerized experiments, American undergraduates and Shuar hunter-horticulturalists predicted the presence or absence of various natural resources (e.g., fruits, bird nests in a forest) and modern ones (e.g., coin tosses, parking spots in a city) in sequences whose patterns were actually generated randomly but which could have been associated with recourse-specific expectations of clumpy or dispersed distributions (Wilke & Barrett, 2009). With the exception of American students predicting series of coin tosses, participants in both populations exhibited positive recency across all the resource types, with the strongest effects associated with instances of natural resources. This suggests that positive recency is a psychological default that evolved as an adaptation to clumpy resource distributions.

1.2. Individual prediction strategies

Past research on pattern perception and prediction has often been mute regarding the actual strategies that people use when making predictions. However, taking a closer look at strategies can provide a better understanding of when and why people exhibit positive or negative recency. Here we consider two commonly employed and well-analyzed strategies. For positively autocorrelated (streaky) sequences, the win-stay/lose-shift strategy (which we will refer to as *stayshift*; Nowak & Sigmund, 1993) performs well: continue predicting the same event as before after a correct prediction and switch after a wrong prediction. For negatively autocorrelated (alternating) sequences, the complementary win-shift/lose-stay strategy (*shiftstay*) is effective (Bicca-Marques, 2005). With these two strategies, one way the positive recency could be manifested is if people use stayshift even in situations where shiftstay would be more adaptive.

1.3. A stronger empirical test of positive recency

The studies described above suggest that people's tendency to see patterns is biased towards perceiving and trying to exploit positively autocorrelated sequences. But how strong is this disposition towards positive recency? Is it powerful enough to lead people to deviate from a behavior that would be optimal from an economic perspective? Specifically, can it lead people to forgo a payoff because they prefer an unpredictable random environment that seems positively autocorrelated over an environment that actually has an exploitable pattern? So far, researchers have usually adopted an experimental design in which participants only saw and predicted one sequence at a time. To test the strength of the positive recency bias, we have developed a design in which participants get to choose whether to predict a binary random sequence of equiprobable and independent events or a simultaneously-displayed sequence of equiprobable but (positively or negatively) autocorrelated events.

This particular design allows investigation of two main predictions regarding positive recency. Given two sequences to choose between, one random and the other autocorrelated, an initially unbiased, but learning, decision maker should eventually choose to predict the events in the autocorrelated sequence—no matter whether it is positively or negatively autocorrelated—because it allows for a prediction accuracy (or payoff) that is above chance level, while the random sequence does not. But starting instead with the assumption that humans are predisposed towards positive recency, we predict two different effects: First, decision makers with a bias towards positive recency are more likely to opt for a positively autocorrelated sequence over the random one, as their payoff will be higher for the former (Hypothesis 1). As this would also hold true for an unbiased or neutral decision maker who just aims towards payoff maximization, the second prediction is a more important test: Decision makers with a bias to expect positively autocorrelated environments will prefer to bet on a random sequence over one with a slight negative autocorrelation (Hypothesis 2), as the former would be perceived as having a "pattern" while the latter appears "random" (Falk & Konold, 1997). Thus, we predict that positive recency induces a fundamental asymmetry in the perception of deviations from randomness (and therefore in the choices of which sequence to predict)—for two sequences equidistant from randomness in terms of positive or negative autocorrelation, streaky/clumpy patterns should be more preferred as compared to alternating/dispersed patterns. We test these two predictions and assess the corresponding choice strategies participants use by analyzing their choice behaviors in a laboratory experiment.

2. Method

To explore the choices and strategies of decision makers predicting sequences of outcomes, we chose a setting for which participants had no prior experience about the underlying sequential distributions: an artificial gambling task. Contrary to the priming of natural resource distributions used by Wilke & Barrett (2009), the current experimental design gave participants the choice to predict the next outcome from two binary sequences generated by novel gambling machines.

2.1. Choice task

Participants in the experiment were invited to the lab where they saw two different "slot" machines next to each other on a computer screen (Fig. 1). Each machine generated a binary sequence of symbols (one symbol per trial) that was displayed on the machine. One machine generated a random sequence drawn from a Bernoulli distribution with the probability of alternation $p_A = .5$ (i.e., zero autocorrelation); the other machine generated a sequence that was either positively or negatively autocorrelated. Note that the serial autocorrelation can also be expressed as the probability of alternation (p_A) based on the following transformation: $r = -2 \cdot (p_A - 0.5)$. Thus, for positive autocorrelation $p_A < .5$ and for negative autocorrelation $p_A > .5$.

The base-rate of both symbols was set to 50% for both machines. Participants had to choose a slot machine on each trial and predict the next symbol that would be displayed by that machine. They indicated the machine they wanted to predict on a given trial by selecting the symbol they thought would be displayed next on that machine (that is, they selected one of four symbols, with two symbols possible for each machine). After they made their choice, the selected machine displayed the next symbol and the other machine remained dormant. Participants received feedback after each of their predictions: If the next-displayed symbol on the selected machine matched their prediction, a green tick mark was displayed on the screen and they earned one token, otherwise, a red cross was displayed and they earned nothing. Each participant made a total of 250 predictions. To reduce participants' working-memory load and to facilitate their learning about the novel patterns, the previous 21 symbols displayed on each machine were shown in the order of their appearance on the corresponding side of the screen.

The side of the screen on which the autocorrelated machine was displayed was counterbalanced between participants. The machine on the left side of the screen was labeled 'Dreammaker' and could display a sun or a moon; the machine on the right side of the screen was labeled 'Fruitshaker' and either displayed a cherry or a peach. To ensure an initial exploration of the sequences, participants went through a training phase in which they were initially constrained to predict 21 rounds on the left machine followed by 21 rounds on the right machine. For each of the remaining 208 rounds they were free to choose between the two machines. Participants were told when the training phase was over and the main experiment started.

To control for participants' prior assumptions about the underlying mechanisms that generated the sequences, they were instructed that one of the slot machines had a flawed random generator such that it generated either positively or negatively autocorrelated sequences (the other machine being properly random). Participants were further informed about the concept of positive and negative autocorrelation and how it allows for improved prediction accuracy. As an incentive to make accurate predictions, they were also told that the top two participants in the experiment who made the most correct predictions would receive a $50 reward. The experimental software was programmed in C#. The study was approved by the Indiana University Institutional Review Board.

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2.2. Alternation rates

The serial autocorrelation *r* (with lag = 1) on the autocorrelated machine varied between participants from .6 (very streaky) to .4 to .2 (slightly streaky) and from -.6 (very dispersed) to -.4 to -.2 (slightly dispersed). The first sequence of 21 symbols on each machine was preset so that the autocorrelation of the displayed symbols would exactly match the intended experimental condition. For the following rounds, the experimental software generated the symbols “on the fly” such that each participant would see a different sequence. While this ensured that the outcome would match the designated autocorrelation over the long run, in the short run the actual alternation rate of the sequences observed by each participant could vary slightly: The actual mean of the autocorrelation across participants in each condition after the initial 42 practice rounds was less than 2% off the intended alternation rate and the upper and lower quartiles were less than 4% off, indicating that the observed sequences actually converged to the intended autocorrelations. Similar results hold for the base rates for the symbols on each machine: Here, for each condition, the means were within a range of ± 3% around 50%. The upper and lower quartiles were less than ± 5% off except for the conditions with $r = \pm.6$, where the quartiles were up to 9% off because here some participants only sampled very few events on the random machine. Table 1 displays examples of sequences with different degrees of positive and negative autocorrelation consisting of 21 symbols each.

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2.3. Participants

A total of 238 participants were recruited from introductory psychology classes at Indiana University, Bloomington. Participants received course credit and the chance to win money. Mean participant age was 19.7 years (*SD* = 1.7 years), and 32% (*N* = 76) were female. There were 24 participants in the condition with $r = .6$, 51 participants with $r = .4$, 44 with $r = .2$, 39 with $r = -.2$, 51 with $r = -.4$, and 29 with $r = -.6$. All participants also saw the random sequence with $r = 0$. The subsample sizes differed slightly to ensure enough statistical power for the conditions with subtler effects according to previous research (Cohen, 1988; Falk & Konold, 1997).

3. Results

3.1. Choice probabilities

All analyses are based on the 208 decisions where participants could freely choose between the two slot machines, resulting in a total of 49,504 choices across all participants. Out of these, 58.7% were on the autocorrelated machine, indicating that the majority of the time participants chose the “correct” (more predictable) machine $t_{237} = 4.7$, $p < .001$. This was not equally the case for all conditions though: For the positively correlated sequences 70.1% of the choices were on the autocorrelated machine rather than the random machine, while for the negatively autocorrelated sequences the percentage dropped to only 47.3%. Thus, participants were more likely to choose to predict the autocorrelated machine if it generated a streaky as compared to an alternating pattern ($t_{236} = 6.7$, $p < .001$). The probabilities of selecting the positively autocorrelated machine were all above 50% ($t_{118} = 8.6$, $p < .001$) (Fig. 2). This supports our first hypothesis. For the moderately negative autocorrelated cases of $r = -.2$ and -.4 the probabilities of choosing the negatively autocorrelated machine were below 50% ($t_{89} = -2.4$, $p = .021$), indicating that in these conditions participants on average preferred betting on the random sequence rather than the alternating sequence. This supports our second hypothesis. (For

r = -.6, participants on average preferred the strongly negatively autocorrelated machine over the random one.)

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In line with the predicted performance differences for positive recency in different environments, the percentage of correct predictions also differed between conditions (Fig. 3). Across all positively autocorrelated sequences, participants predicted 59.2% of the outcomes correctly as compared to only 52.9% for the negatively autocorrelated ones (t_{236} = 5.8, p < .001). Thus, participants were more successful at predicting the positively autocorrelated sequences than the negatively correlated ones, again reflecting positive recency. The mean prediction accuracy for random sequences was 49.8% (*SD* = 6.5%), and thus, as expected, did not exceed chance level (t_{237} = -.42, p = .674).

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3.2. Prediction strategies

To explore the individual prediction strategies being used, we further assessed how often participants stayed on the same symbol (on the same machine) from one prediction to the next and how often they shifted to another symbol, depending on the success of their previous prediction. A shift was counted if they switched to the other symbol on the same machine (results were similar when we also included switches to the other machine, which occurred in 11.5% of the cases). In the conditions with positively autocorrelated sequences, 70.3% of the choices on the autocorrelated machine were in line with the appropriate win-stay/lose-shift (stayshift) strategy, whereas for negatively correlated sequences, only 48.5% of the choices matched the appropriate win-shift/lose-stay (shiftstay) strategy ($t_{230} = -7.5$, $p < .001$). As illustrated in Fig. 4, for negative autocorrelations of $r = -.2$ the adaptive shiftstay strategy was only used for 38.9% of the choices on average, which was below chance level of 50% ($t_{37} = -4.2$, $p < .001$). There was also a main effect of the autocorrelation such that for both conditions the use of the appropriate strategy on the autocorrelated machine linearly increased with the absolute value of the autocorrelation ($F_{2,226} = 28.9$, $p < .001$).

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For predictions on the random machine, 60.8% of all choices match stayshift, significantly higher than the chance level of 50% ($t_{209} = 9.3$, $p < .001$). The predominant use of stayshift on the random machine holds across all experimental conditions. This indicates that participants had a general tendency to use stayshift, the appropriate strategy for streaky environments, as a default strategy in all cases, which could explain their inferior performance for negative autocorrelations where shiftstay would have been the appropriate strategy. A closer look at the data further revealed that for choices on the autocorrelated machine participants’ reactions following losses (wrong predictions) were less adaptive than their responses after wins. In particular, after losing on the previous trial, participants applied the appropriate strategy ("stay" in the conditions with negative autocorrelation, "switch" in the conditions with positive autocorrelation) in 54.9% of the cases on average whereas after winning, they applied the appropriate strategy ("switch" for negative autocorrelation, "stay" for positive autocorrelation) in 62.2% of the cases ($t_{231} = 4.7$, $p < .001$).

3.3. Behavior change over time

To test whether participants improved their accuracy or their strategy use over time, we counted how often the autocorrelated machine got selected across the 208 rounds of the experiment. In the conditions with medium ($r = .4$) and high ($r = .6$) positive autocorrelation the probability of selecting the autocorrelated machine was positively correlated with the number of rounds played, $r = .86$ ($p < .001$) and $r = .53$ ($p < .001$) respectively (Fig. 5). Participants in the condition with high negative autocorrelation ($r = -.6$) also became more likely to place their bets on the autocorrelated machine over time ($r = .66$, $p < .001$), indicating that they learned appropriately about the regularity of the environment.

Contrary to this, for conditions with small and medium negative autocorrelation ($r = -.2$ and $-.4$), the probability of selecting the autocorrelated machine was negatively correlated with the number of rounds played, with $r = -.22$ ($p = .002$) and $r = -.41$ ($p < .001$) respectively. Thus, over the course of as many as 250 rounds, feedback in those conditions on average did not improve the choices but made performance worse.

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4. Discussion

When faced with a choice between predicting random sequences versus positively autocorrelated ones, participants in our experiment were more likely to place bets on the autocorrelated sequences, which led to payoffs above chance level (Hypothesis 1). This tendency became stronger as the level of positive autocorrelation increased. In contrast to this, participants in conditions with moderately negative autocorrelations were less likely to bet on the autocorrelated machines, which in turn led them to lower payoffs (Hypothesis 2). Those who saw a random sequence next to one with slight negative autocorrelation on average actively preferred the random sequence, and thus missed the opportunity to get a payoff above chance level. This preference even increased over the course of the experiment, suggesting that feedback could worsen rather than improve participants' choices. Together, these results, in line with those by others (Tyszka et al., 2008; Kareev, 1995; Oskarsson et al., 2009) support our two predictions and provide strong evidence for positive recency according to which people are more likely to look for, detect, and exploit streaky sequences as compared to alternating ones—an adaptive strategy in environments characterized by clumpy resources (Wilke & Barrett, 2009).

This evidence of negative autocorrelation and the lack of improvement over time was maladaptive in the sense that it did not maximize payoffs and violated the rational standard of Bayesian updating. In other words, an optimal, payoff-maximizing agent would have learned to exploit the negatively correlated sequences by exhibiting negative recency and would have left the experiment with a greater potential payoff. These data provide just the kind of evidence that McKay and Efferson (2010) argued is necessary to distinguish cognitive biases as outlined in the error management framework (Haselton & Buss, 2000; Haselton & Nettle, 2006) from mere behavioral biases that could also be explained within existing theoretical frameworks of utility maximization.

As noted in the introduction, one explanation for the strong prevalence of positive recency would be that it proved adaptive in ancestrally important environments that were positively autocorrelated. It can be seen as a form of area-restricted search behavior commonly found in foraging animals and also seen in human cognition (Hills, 2006)—essentially, once the organism is in a resource patch, it should expect to continue to find resources in that patch, and so restrict search to that area, until it receives evidence otherwise (failing to find more resources). Under this explanation, showing "erroneous" hot hand or gambler's fallacy behavior is the result of testing an otherwise ecologically rational strategy in an environment for which it is not designed (Gigerenzer, Todd, and the ABC Research Group, 1999). To further explore this possibility, we need more investigation of the structure of ancestral (and related modern) environments to determine the extent to which streaky/clumpy and alternating/dispersed environments may have exerted selective pressure on the design of human prediction abilities.

On a general level, presumably the prevalence of positive recency in our data occurred because participants perceived the random sequence as streaky and/or the sequence with (slight) negative autocorrelation as being random (Falk & Konold, 1997). However, this explanation is difficult to test directly with the data at hand. For instance, people’s assumptions about possible patterns also depend on what they think about the process that generated the sequence of events (Ayton & Fisher, 2004; Tyszka et al., 2008). However, when the data generating process was left unspecified in the present experiment, most people still exhibited positive recency, again pointing to its use as a default assumption. If anything, the fact that participants had to bet on inanimate slot machines that resemble the random process of a roulette wheel could have triggered the gambler’s fallacy (Reichenbach, 1949), but it generally did not.

The patterns we observed could also stem from other reasons for participants using the particular prediction strategies they employed. Most participants tended to use stayshift even though this strategy is specifically appropriate for positively autocorrelated sequences and leads to inferior performance in the case of negative autocorrelation. A preference for stayshift seems plausible because it can be seen as a special instance of the 'Law of Effect', according to which rewarded behaviors are subsequently shown more often than non-rewarded behaviors (Thorndike, 1911). Operant conditioning relies on win-stay behavior, and to some extent also on lose-shift as when the probability of a behavior is decreased by withholding reinforcement (Skinner, 1953). A variant of stayshift, known as the 'Pavlov' strategy, also works well in strategic interactions like the prisoner’s dilemma where it has been shown to be more robust than many other strategies (Nowak & Sigmund, 1993). Thus, it can be speculated that win-stay (and to some extent also lose-shift) act as default strategies whereas lose-stay and win-shift strategies might be more difficult to acquire (see Wilke & Barrett, 2009 for a similar argument).

5. Conclusions

Detecting contingencies and patterns in one's environment is an important aspect of adaptive behavior. If those contingencies arise from searching for resources such as animals and plants that tend to cluster together in space and time (Bell, 1991; Krause & Ruxton, 2002), then expecting positive autocorrelations in the environment will lead to greater success than having other expectations. The successful detection and exploitation of such relationships thus depends on both the objective structure of the environment and also on people’s expectations and prediction strategies applied to that environment (Alloy & Tabachnik, 1984)—the two components, mind and environment, have to fit together for adaptive, ecologically rational behavior to arise (Todd & Gigerenzer, 2007). Our results suggest that people have a strong prior or default expectation that sequences of events in their environment are positively autocorrelated—strong enough to lead them to prefer random sequences over alternating ones that they could better predict. Furthermore, this prior expectation appears difficult to overcome even with repeated feedback and the opportunity for direct comparison between different sequences. Such positive recency helps people to better detect and exploit clumped or streaky sequences that are common in nature, at the same time producing the biased apophenia—seeing patterns in random sequences and randomness in negatively-autocorrelated sequences—that is often observed in the lab.

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Table legends

Table 1: Examples of sequences of 21 symbols each with different degrees of negative and positive autocorrelation.

Figure legends

Figure 1: Screenshot of the experimental setup for selecting and predicting one of two slot-machine sequences.

Figure 2: Probability of choosing the autocorrelated sequence over the random sequence averaged across all participants in each condition. Error bars indicate 95% bootstrapped confidence intervals.

Figure 3: Percentage of correct predictions averaged across all participants in each condition. Error bars indicate 95% bootstrapped confidence intervals.

Figure 4: Percentage of choices on the autocorrelated machine that are in line with the appropriate strategy (win-stay/lose-shift for positive autocorrelations and win-shift/lose-stay for negative autocorrelations) averaged across all participants in each condition. Error bars indicate 95% bootstrapped confidence intervals.

Figure 5: Percentage of correct predictions averaged across all participants in each condition across time. The successive points (left to right) in each group of four show the mean over trials 1-52, 53-104, 105-156, and 157-208 respectively. Correlation coefficients indicate the linear trend of selecting the autocorrelated machine, estimated across all participants and all 208 decisions in each condition. Asterisks (*) indicate $p < .01$.

TABLE 1

Negative autocorrelation	r = -.6	O X X O O X O X O X O X X O X O O X O X O
	r = -.4	X O X X O X X O X O O O O X O X X O X O X
	r = -.2	X X O X X O X O X O X X O O X X O O O O X
Positive autocorrelation	r = .2	X O X X X O X O O O X X X X O O O O O X X
	r = .4	O X X X O O X X X X O O X X X O O O O O O
	r = .6	X X X X X X X O O O O O O O O X O O X X X

FIGURE 1

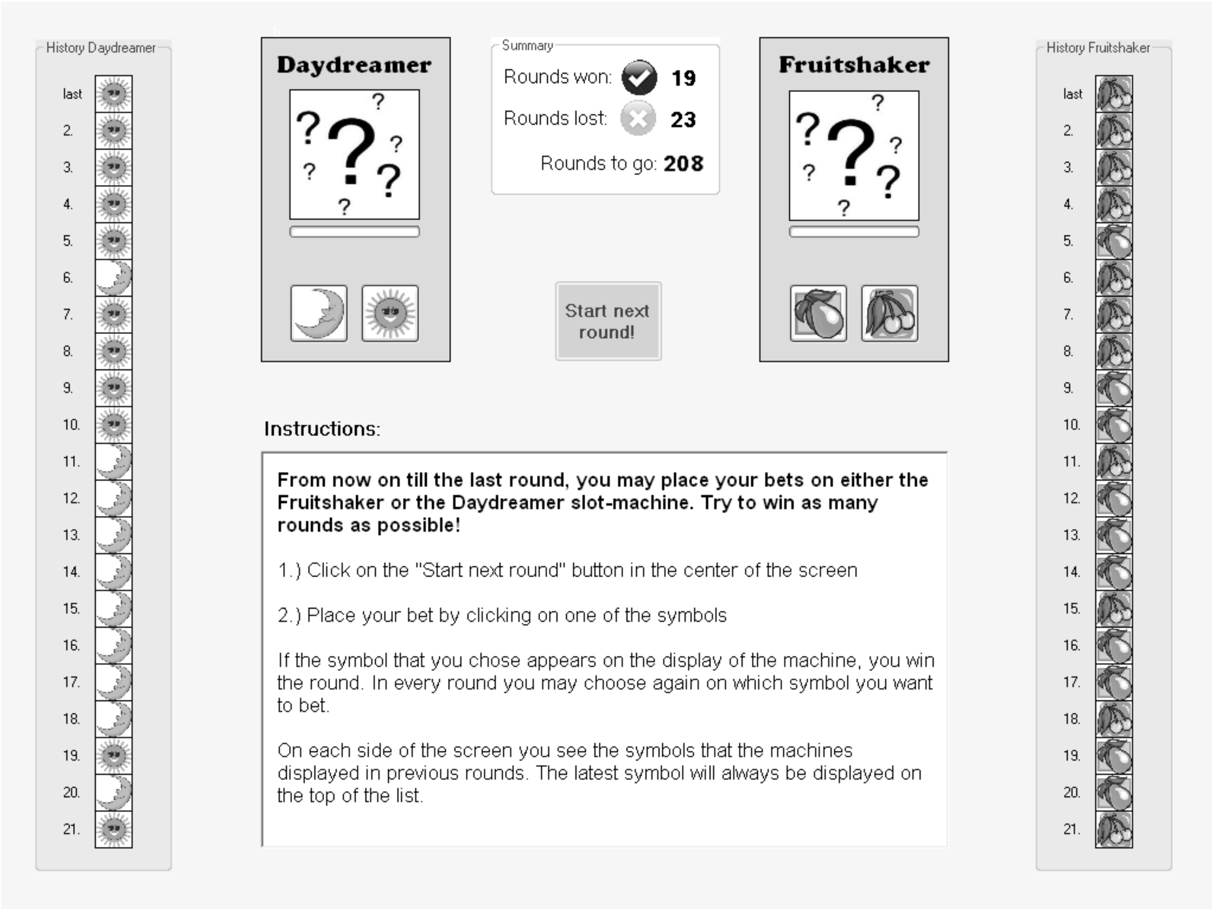
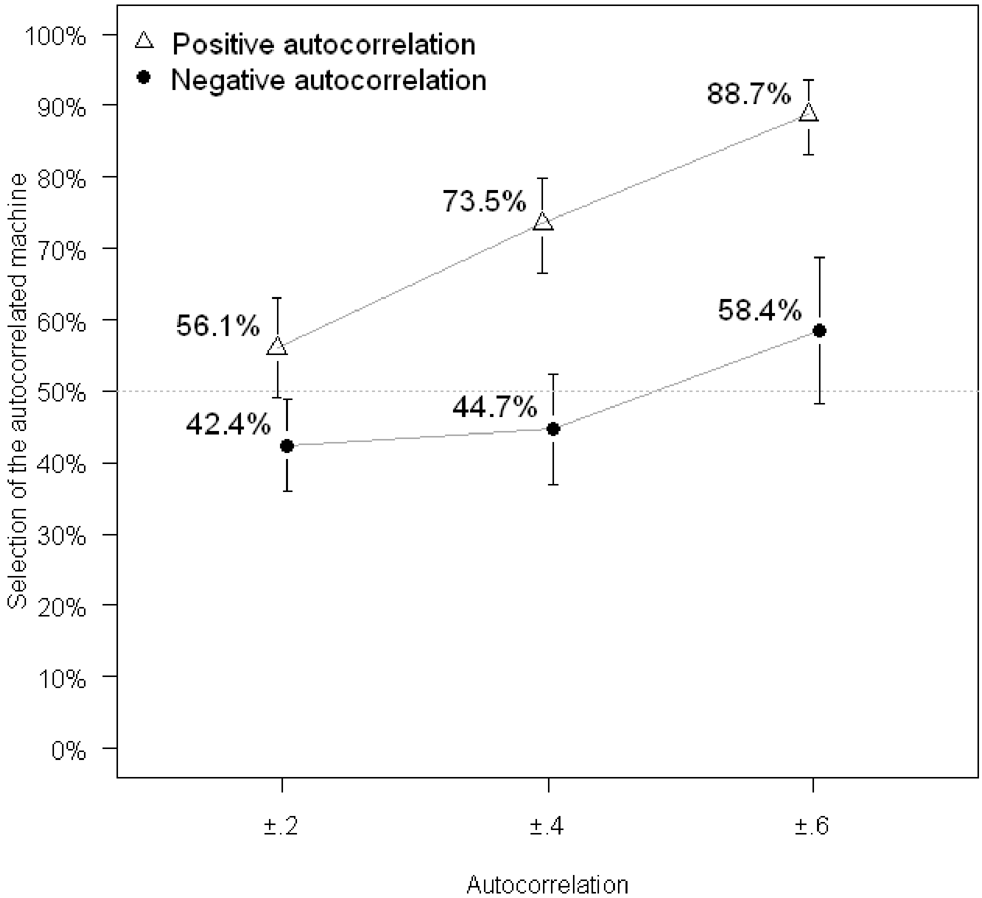

History Daydreamer
last
2.
3.
4.
5.
6.
7.
8.
9.
10.
11.
12.
13.
14.
15.
16.
17.
18.
19.
20.
21.
Daydreamer
Summary
Rounds won: 19
Rounds lost: 23
Rounds to go: 208
Start next round!
Fruitshaker
History Fruitshaker
last
2.
3.
4.
5.
6.
7.
8.
9.
10.
11.
12.
13.
14.
15.
16.
17.
18.
19.
20.
21.
Instructions:
From now on till the last round, you may place your bets on either the Fruitshaker or the Daydreamer slot-machine. Try to win as many rounds as possible!
1.) Click on the "Start next round" button in the center of the screen
2.) Place your bet by clicking on one of the symbols
If the symbol that you chose appears on the display of the machine, you win the round. In every round you may choose again on which symbol you want to bet.
On each side of the screen you see the symbols that the machines displayed in previous rounds. The latest symbol will always be displayed on the top of the list.

FIGURE 2



Positive autocorrelation
Negative autocorrelation
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Selection of the autocorrelated machine
56.1%
73.5%
88.7%
42.4%
44.7%
58.4%
±.2
±.4
±.6
Autocorrelation

FIGURE 3

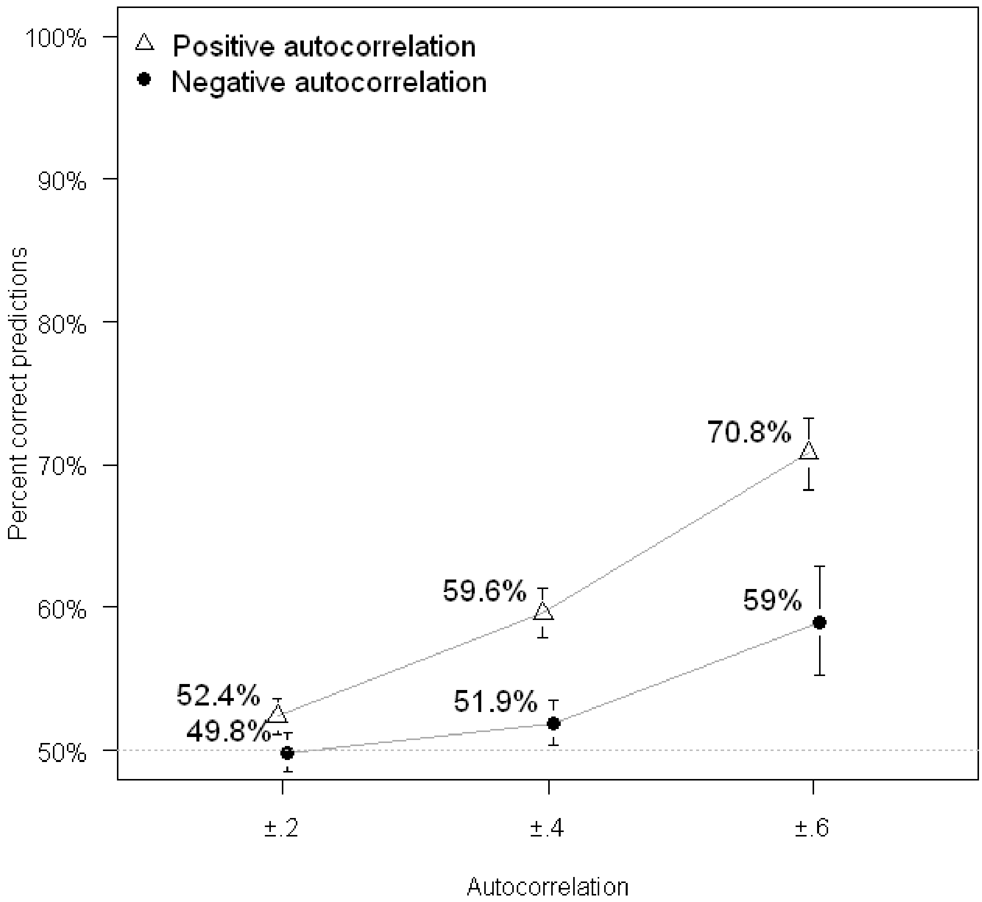

Positive autocorrelation
Negative autocorrelation
100%
90%
80%
70%
60%
50%
Percent correct predictions
70.8%
59.6%
59%
52.4%
51.9%
49.8%
±.2
±.4
±.6
Autocorrelation

FIGURE 4

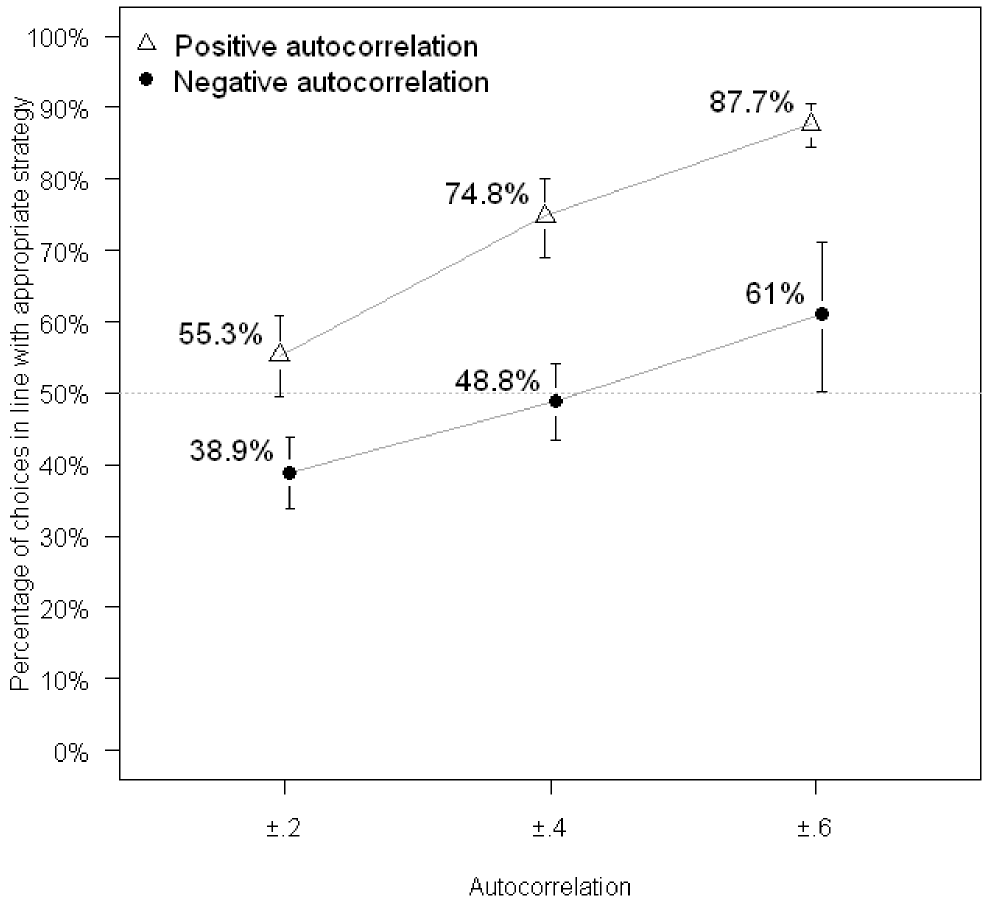
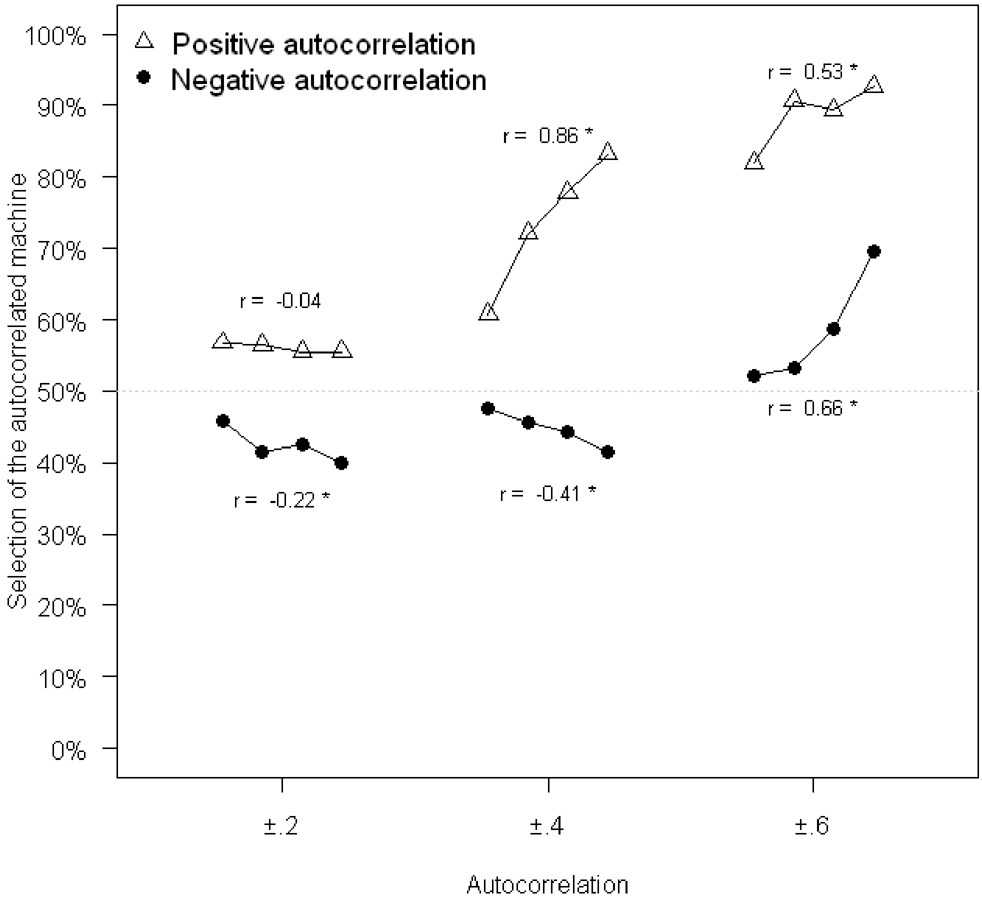

Positive autocorrelation
Negative autocorrelation
87.7%
74.8%
61%
55.3%
48.8%
38.9%
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Percentage of choices in line with appropriate strategy
±.2
±.4
±.6
Autocorrelation

FIGURE 5



Positive autocorrelation
Negative autocorrelation
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Selection of the autocorrelated machine
r = -0.04
r = -0.22 *
r = 0.86 *
r = -0.41 *
r = 0.53 *
r = 0.66 *
±.2
±.4
±.6
Autocorrelation