

# Fun in Slots

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**Abstract— People play games for fun. Yet we are lacking a fundamental understanding of what fun is and how fun works in games and other media. For example, why do thousands of people spend millions of dollars playing slot machines, especially when most know they will lose money in the long run? To answer this question, I present an aesthetic analysis of slot play using a Bayesian-information approach. The finding is that fun in slots can be seen as arising from a difference in information gained from good versus bad outcomes. This difference is modeled by marginal entropies and the result is a measure of fun in slot play, showing for what range of payoff probabilities slots are fun and at what probability they are most fun. The approach is extended to games of skill and the same Bayesian-information theory is used to derive computational measures of fun in these games.**

## I. INTRODUCTION

FUN is serious business, especially in the entertainment industry. But games are also used in other industries for testing-out strategies and training of employees, and real fights against competitors and enemies are driven by feelings of tension and pleasure. Yet these feelings and fun are poorly understood, especially from a computational perspective. This may be acceptable and even desirable for game consumers, but it is not acceptable for game designers if they are to advance the state of their art and practice through systematic engineering.

This paper takes a small step towards understanding fun in games, with a focus on gambling in slot machines. The approach is one of *computational aesthetics*, which is relevant to *computational intelligence* because human emotions affect human cognition, and vice versa. From a practical perspective, aesthetics are important to efforts aimed at: (i) designing machines that adapt to the feelings of users, i.e., in human-computer interface design, and (ii) designing machines that can simulate human behavior, i.e., in artificially intelligent agents. The bottom line is that human actions are driven by both thinking and feelings, in both occupational work and recreational play; hence a computational understanding of intelligence must include a computational understanding of aesthetics.

The question is: Why do people play gambling games like slot machines, even when they know they will lose in the long run? Clearly they play for *fun*, but then what is fun?

In one answer, Koster [1] writes, “Fun is just another word for learning” (pg. 46); “Games that are too hard kind of bore me, and games that are too easy also kind of bore me.” (pg. 10). But all learning is not so *fun*, and “Goldilocks” statements about people liking things “not too hard or too easy” are really just common sense.

Slot machines are a good example because playing them is clearly fun for many people, and yet the game does not seem to be much of a *learning challenge*. In fact it is rather remarkable that slots, which are so *repetitive* [2], are such a popular amusement for cognitive intelligence. Therefore, a theory of fun must address the pleasure that comes from repetition as well as the pleasure that comes from a learning challenge; plus slots are not fun for everyone so personal preferences must be part of the equation, too.

Here I develop an equation,  $f = G * E + G' * E'$ , for fun in slots, based on a general theory of aesthetic experience called *EVE'* [3]. According to *EVE'*, fun comprises two types of pleasure, each stemming from subjective success in different but related types of cognitive processing. One type is pleasure that arises from success in forward-looking *Expectations* (E) of what *will* happen in a media experience (e.g., game). The other type is pleasure-prime that arises from success in backward-looking *Explanations* (E') of what *has* happened in a media experience (e.g., game). The two are related by *Violations* (V) of E that create opportunities for E' in the sequence E-V-E'.

Here, following *EVE'*, I argue that fun in slots is a *tradeoff* between pleasure (p) at E and pleasure-prime (p') at E', where p corresponds roughly to the idea of *repetition* [2] and p' corresponds roughly to the idea of a *learning challenge* [1]. In expanding and evaluating the equation,  $f = G * E + G' * E'$ , I show that while fun in slots involves both repetition at E and a learning challenge at E', logically most of the fun *must come* from E'. I also discuss how E' itself is governed by a tradeoff between good/bad outcomes, and how personal preferences and a *sense of humor* affect the computed measure of fun.

The analysis is generalized beyond slots to games of skill, and the same basic equation is shown to apply. The main finding is that fun in slots and other games can be modeled and measured as a difference in information gained from good outcomes versus bad outcomes, where information is measured by marginal entropy. The net fun in games is made possible by *Violations* (V) of *Expectations* (E) for good and bad outcomes, which create tension that is ultimately resolved with pleasurable or displeasurable *Explanations* (E').

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## II. DISCUSSION

When used in its most general sense, the term “gambling” refers to games in which the outcome is unknown – and in that sense most games can be considered gambling games (see Section III). When used in a more specific sense, the term “gambling” refers to the genre of game play found at casinos and race tracks and other venues where one pays some amount of money  $A$  (ante) with the chance  $P < 1$  of getting a payoff  $J$  (jackpot) where  $J > A$ .

Financially speaking, casino gambling is a zero-sum game because whatever is lost by one player is gained by another player, i.e., “the house”. Psychologically speaking, the same is not true, and in fact the casino industry thrives on a *win-win* phenomenon whereby the house wins money and the player wins pleasure. That is, people play even though they lose money, and the only plausible explanation for this rather puzzling behavior is that they must be having some fun.

As a simple and concrete example, consider a “fair” slot machine in which the player antes one coin and there are only two possible outcomes: either the player gets a jackpot of  $J$  coins or the player gets nothing. The machine is “fair”, because  $J=1/P$  where  $P$  is the probability of hitting the jackpot. Of course most slots are more complex than this because there are a number of payoffs  $\{J_1, J_2, \dots, J_n\}$ , each with a corresponding  $P$  that is equal or at least roughly equal to  $1/J$ , i.e.,  $\{P_1, P_2, \dots, P_n\}$ . Real slots are also not “fair”, because the house takes a percentage (typically around 5%), and so the payoffs are reduced accordingly.

Nevertheless, here I analyze a test tube game in which there is only one  $P$  and  $J=1/P$ . The results generalize to the more complex case simply by treating a real machine as a set of single- $P$  machines with various  $P$ s.

From a normative perspective, the player’s expected utility in this slot game is zero because the average outcome is  $P*J=1$ , which equals the ante of one coin. Yet, from a cognitive perspective, the player must be getting some sort of subjective *utility* or net fun, otherwise he would not play. Here it is relevant that research in the field of behavioral decision making [4] has shown that people have *subjective (cognitive) utilities* that deviate from *objective (normative) utilities*. That is, the mental value of a dollar gained or lost, called the marginal utility, is more or less than a dollar.

But this only makes fun in slots more puzzling, since the cognitive deviations from normative behavior are usually such that people are *risk averse* – which means that they not only avoid “fair” bets but actually *require better than even odds* in gambling choices. This finding is exactly the opposite of what one would expect to find if cognitive biases in subjective utility were the reason that people play slots. For example, a typical subjective-versus-objective utility function [4] is shown in Fig. 1. Here the subjective utility (y-axis) increases with objective utility (x-axis), but the slope decreases as utility increases, which means that people are risk averse.

The applicability of such curves to human behavior in decision gambles has been well established by numerous studies [4]. The underlying intuition, which says that a dollar is worth less as the number of dollars increases, can be traced back at least as far as Bernoulli [5] who proposed that subjective utility is roughly proportional to the *logarithm* of objective utility – as plotted in Fig. 1.

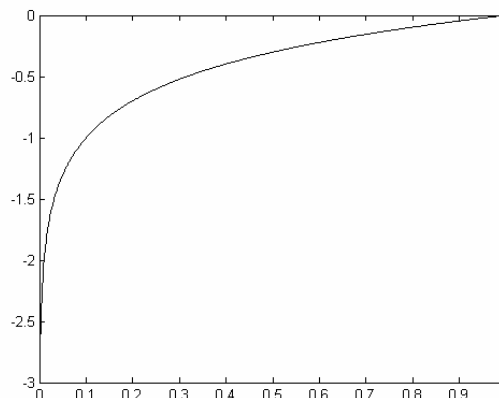


Fig. 1. A typical utility curve, plotting subjective utility (y-axis) versus objective utility (x-axis) as  $y = \log x$ .

The point here is that people have been shown to be risk averse in gambling studies, which suggests that they would not play slots even if the slots were known to be “fair”, let alone if the odds were known to be stacked against them. But people do play, and this makes the slot craze even harder to explain, i.e., it further highlights the need for a computational understanding of fun in games.

Below I present an analysis that leads to a plausible explanation for why people play slots. The approach uses a Bayesian-information theory, and the results suggest that the reason people play slots is that they get more information from winning jackpots than they do from losing antes, i.e., the net fun comes from an informational gain even when there is no financial gain. And since net fun or pleasure can offset the displeasure of losing money, this finding may also explain why people play casino slot machines that are not even “fair”. In short, the idea is to analyze slots as an *informational* game, which a player *can* win, rather than a *financial* game, which a player *cannot* win.

### A. Expectations

To begin the analysis, consider a player’s beliefs *before* a payoff. For the fair machine (above), a player’s *Expectation* ( $E$ ) of a jackpot  $J$  can be modeled as  $\log P$  [6]. Note that this is an *informational* measure of expectation that refers to the occurrence of the event (jackpot), not a *financial* measure of either the amount of the jackpot  $J$  or the expected utility of the jackpot  $P*J$ .

Note also that the measure of E is  $\log P$  rather than raw P. Referring to Fig. 1,  $\log P$  increases monotonically with P, as it should if it is to be a measure of expectation. However, there are three reasons [3] for using  $\log P$  instead of raw P, namely: (i)  $\log P$  is the information-theoretic measure of expectation that gives rise to a measure of *entropy* [6], (ii)  $\log P$  is consistent with common wisdom [5] and experiments [4] on subjective utility, and (iii)  $\log P$  and its additive inverse  $\log 1/P = -\log P$  are “linear” [6] measures that are symmetric about an anchor of zero – and cognitive processes for measuring quantities are known to be governed by a number “line” [7].

Here, the player expects to win a jackpot with probability P and expects to win nothing with probability 1-P. So, in information-theoretic terms:  $E_J = \log P$  provides a mathematical measure of success in forming *Expectations* when the payoff J is actually observed; and  $E_0 = \log (1-P)$  provides a mathematical measure of success in forming *Expectations* when the payoff 0 is actually observed. Thus, weighing the E for each informational outcome (J or 0) by its frequency of occurrence (P or 1-P) in repeated play, the total measure of success in forming *Expectations* (E) while playing slots is given as follows:

$$E = \{E_J + E_0\} = \{P * \log P + (1-P) * \log (1-P)\}$$

Notice that this expression is equal to the negative of total entropy for the set of possible outcomes  $\{0, J\}$ , since the entropy for a set  $\{s_i\}$  of i signals (outcomes) with probabilities  $\{P_i\}$  is defined as  $-\sum_i P_i * \log P_i$  [6]. The plot for E in Fig. 2 shows that E is highest at P=0 and P=1, while E is lowest at P=0.5. That is, the maximum negative-entropy (minimum entropy) occurs at P=0 and P=1 where the machine is completely predictable, while the minimum negative-entropy (maximum entropy) occurs at P=0.5 where the machine is completely random.

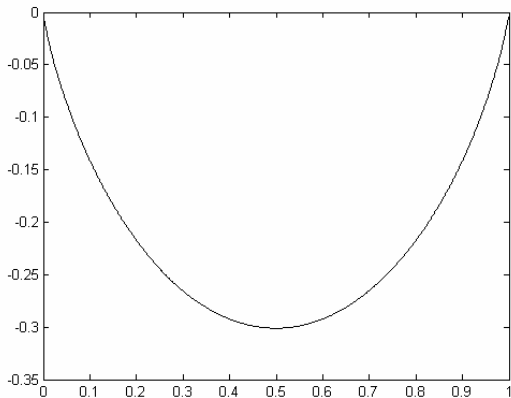


Fig. 2. A plot of the function E in slots. E measures the average rate of success in forming *Expectations* for payoffs J and 0.

In EVE' [3], this measure E of success in forming *Expectations* gives rise to *pleasure* (p). An example is the pleasure that people get from listening to the same songs over and over again, i.e., because they like hearing the notes that they expect to hear. Now, while this is clearly part of an aesthetic experience, it is certainly not the whole story, as we know from the fact that sometimes people like to hear new songs. And, in the case of slots, if all the pleasure came from success at E then, as shown in Fig. 2, people would prefer to play slot machines that are completely predictable – which is obviously not the preference observed at casinos.

### B. Explanations

According to EVE' [3], the rest of the story after E is V and E'. That is, incurring a *Violation* (V) of an *Expectation* (E) will create *tension* – which in turn leads to *pleasure-prime* (p') if and when the tension is resolved by an *Explanation* (E'). An example is the release of tension that causes laughter (*pleasure*) when one “gets” a joke in comedy, which comes after a punch line (*Violation*) but only when the audience “gets it” (*Explanation*).

Thus, pleasure at E and pleasure-prime at E' are both part of the aesthetic equation modeled by EVE'. The two pleasures (p and p') are different, because pleasure p is related to *avoiding Violations* while pleasure-prime p' is related to *incurring Violations*, but they are both part of total pleasure.

To complete the story of EVE' in slots, consider a player's belief *after* a payoff. In either case, payoff J or payoff 0, there will be some *Violation* (V) of *Expectation* (E) because the outcome actually occurred with probability 1 and yet the modeled probability was <1; either P (for payoff J) or 1-P (for payoff 0). Because payoff J is expected with probability P, the measure of *Violation* when payoff J occurs is as follows:  $V_J = \log (1/P) = \log 1 - \log P = -\log P$ . Likewise, because payoff 0 is expected with probability 1-P, the measure of *Violation* when payoff 0 occurs is as follows:  $V_0 = \log (1/(1-P)) = \log 1 - \log (1-P) = -\log (1-P)$ .

Now for either outcome (J or 0), the player experiences both a measure of E and a measure of  $V = -E$ . The E causes pleasure (see above) and the V causes tension which, if resolved by E', leads to pleasure-prime. Conceptually, E and E' are different in that E (before V) involves the *forward-looking Expectation* of possible outcomes, while E' (after V) involves a *backward-looking Explanation* of the actual outcome. Computationally, the equation for E can be written from information theory (see above), but the equation for E' must apply Bayesian theory. That is, using H (hypothesis) to denote a player's *mental model* of cause and effect in the game: E involves *predicting* the likelihood of a datum  $D_i$  in the set  $\{D_i\}$  of possible outcomes, given a set of hypotheses  $\{H_k\}$ . Conversely, E' involves *perceiving* the most likely hypothesis  $H_k$  in the set  $\{H_k\}$ , given the actual datum  $D_i$ . In the latter case, for E', perception can be modeled as a process of Bayesian inference [8].

The basic difference between  $E$  and  $E'$  is that  $E$  is governed by likelihoods of the form  $P(D_i|H_k)$ , while  $E'$  is governed by posteriors of the form  $P(H_k|D_i)$ . The details are explained elsewhere [3], [9], [10], but here for slots the Bayesian analysis is simplified by the fact that there are only two hypotheses, denoted  $L = \text{“good luck”}$  or  $\sim L = \text{“bad luck”}$ . Using  $\sim J$  to denote a payoff of 0, the priors before each outcome are  $P(L)=P$  and  $P(\sim L)=1-P$ , and the likelihoods are  $P(J|L)=1$ ,  $P(J|\sim L)=0$ ,  $P(\sim J|\sim L)=1$  and  $P(\sim J|L)=0$ . Now the problem is to compute the posteriors  $P(L|J)$ ,  $P(\sim L|J)$ ,  $P(\sim L|\sim J)$  and  $P(L|\sim J)$ , which can be done with Bayes Rule.

By Bayes Rule,  $P(L|J) = P(L)*P(J|L) / [P(L)*P(J|L) + P(\sim L)*P(J|\sim L)] = (P*1)/(P*1+(1-P)*0) = 1$ , and similarly  $P(\sim L|J)=0$ ,  $P(\sim L|\sim J)=1$  and  $P(L|\sim J)=0$ . Thus, for this special case of 0/1 likelihoods, the posteriors are simply equal to the corresponding likelihoods. In short, a good outcome (payoff  $J$ ) is explained as “good luck” with posterior probability 1,  $P(L|J)=1$ , and a bad outcome (payoff 0) is explained as “bad luck” with posterior probability 1,  $P(\sim L|\sim J)=1$ .

Since the posterior Explanation of a Violation in slots is equal to 1, the *tension* of the Violation will be completely resolved [3] such that  $E'=V$ . But here I assume that the resolution will give rise to *pleasure* when  $P(L|J)=1$ , and *displeasure* when  $P(\sim L|\sim J)=1$ . That is,  $L$  is like “getting” a good joke, which feels good, and  $\sim L$  is like “getting” a bad joke, which feels bad, so  $L$  and  $\sim L$  lead to pleasure and displeasure, respectively.

Thus, weighing each  $E'=V$  by its frequency (probability) of occurrence in repeated play, and negating the measure  $E'_0$  for the case of payoff 0 because it give rise to *displeasure*, the total measure of success in forming *pleasurable* Explanations is given as follows:

$$E' = \{E'_J - E'_0\} = -\{P * \log P - (1-P) * \log (1-P)\}$$

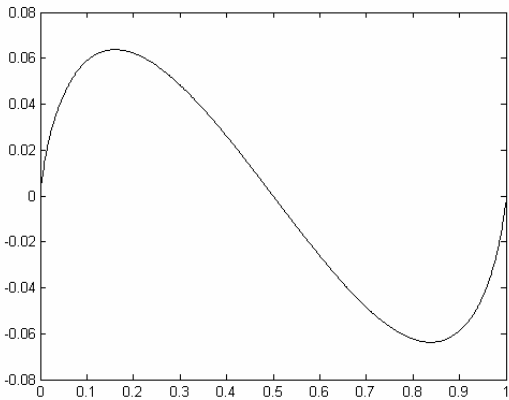


Fig. 3. A plot of the function  $E'$  in slots.  $E'$  measures the average rate of success in forming pleasurable Explanations after Violations of Expectations.

The result, plotted in Fig. 3, shows that  $E' > 0$  when  $P < 0.5$  and  $E'$  is maximized at a  $P$  value of about 0.15.

Notice that an implicit assumption in the above expression for  $E'$  is that *pleasure* and *displeasure* are equally weighted. That is, the equation assumes that resolving a unit of tension in a good way (pleasure), and resolving a unit of tension in a bad way (displeasure), are equal in absolute value. But in fact this may not be so, and it clearly depends on the personal *preferences* of a particular player. Said another way, different people may have different tastes for good/bad payoffs, which by analogy to comedy might be called their *sense of humor* in the game of slots. Thus, the expression for  $E'$  should really be written as follows:

$$E' = -\{H^+ * P * \log P - H^- * (1-P) * \log (1-P)\}$$

where  $H^+$  and  $H^-$  are weighting factors that account for the player’s sense of humor in slots,  $0 \leq H^+ \leq 1$  and  $0 \leq H^- \leq 1$ .

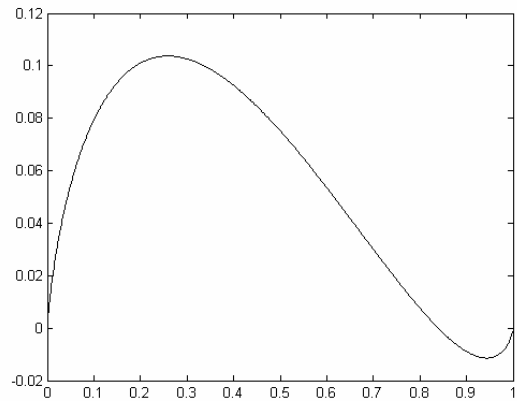


Fig. 4. A plot of the function  $E'$  in slots for a player with a good sense of slot humor.

For example, if a person has a good sense of slot humor, which might be described in behavioral terms as a positive disposition because one likes good outcomes more than one dislikes bad outcomes, then  $H^+ > H^-$ . Conversely, if a player has a bad sense of slot humor, which might be described in behavioral terms as a negative disposition, then  $H^- > H^+$ . To see the effect on the measure of  $E'$ , the above equation is plotted for two cases:  $H^+/H^- = 1.0/0.5$  in Fig. 4 and  $H^+/H^- = 0.5/1.0$  in Fig. 5. These plots show how the personality of the player, or sense of slot humor if you will, affects  $E'$  by magnifying and shifting the player to either the left or the right of the average curve shown in Fig. 3.

Now, putting  $E$  and  $E'$  together, the total pleasure or *fun* ( $f$ ) from playing slots is given as follows:

$$f = G * E + G' * E'$$

where  $E$  and  $E'$  are measures of success in forming Expectations ( $E$ ) and Explanations ( $E'$ ). Here,  $G$  and  $G'$  are scaling factors that translate a level of success ( $E$  or  $E'$ ) to a unit of pleasure ( $p$  or  $p'$ ). They are similar to the factors  $H^-$  and  $H^+$  above in that they account for personal preferences. However, while  $H^-$  and  $H^+$  are concerned with a player's preferred mental *attitude* in  $E'$ ,  $G$  and  $G'$  are concerned with a player's preferred mode of *processing* in  $E$  versus  $E'$ , i.e., the relative enjoyment they get from success in forming Expectations ( $E$ ) versus Explanations ( $E'$ ).

Finally, substituting the measures of  $E$  and  $E'$  derived above, the total fun ( $f$ ) can be written as follows:

$$f = G * \{P * \log P + (1-P) * \log (1-P)\} + \\ - G' * \{H^+ * P * \log P - H^- * (1-P) * \log (1-P)\}$$

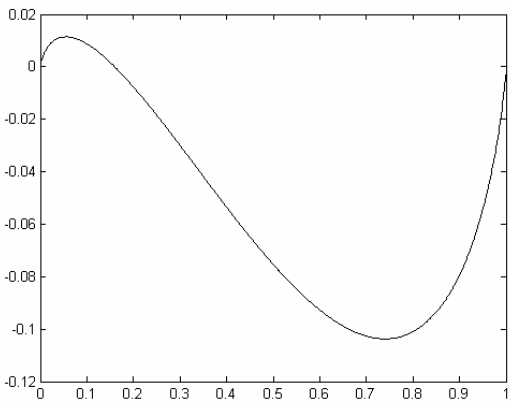


Fig. 5. A plot of the function  $E'$  in slots for a player with a bad sense of slot humor.

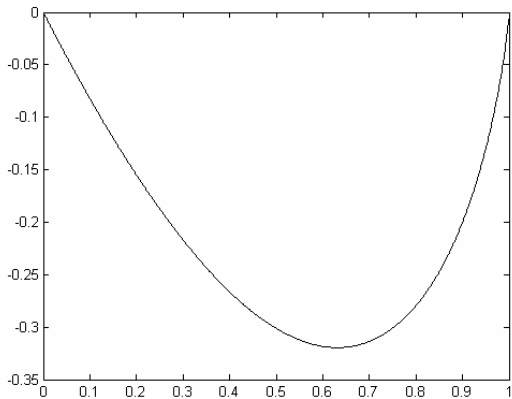


Fig. 6. A plot of the fun function  $f$  for the case where the scaling factors for  $E$  and  $E'$  are  $G=G'$ , showing that fun is negative.

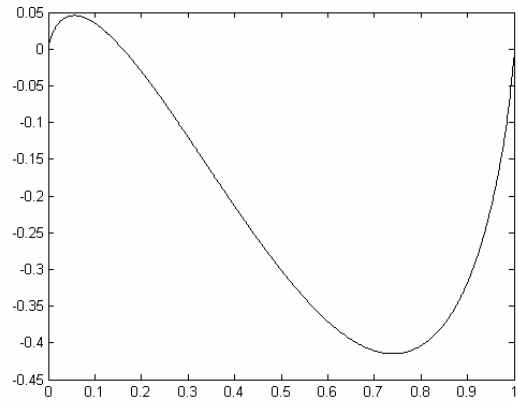


Fig. 7. A plot of the fun function  $f$ , where the scaling factors for  $E$  and  $E'$  are  $G/G'=1/3$ , showing that fun is positive for  $0 < P < 0.2$  and peaked at  $P=0.05$ .

Here it is useful to examine some specific cases for  $H^-/H^+$  and  $G/G'$  to see how fun varies. First, assume that  $H^- = H^+ = 1$  and  $G = G' = 1$ . Then, fun is the sum of Fig. 2 for  $E$  and Fig. 3 for  $E'$ , as shown in Fig. 6. In this case (Fig. 6) we see that  $p$  dominates  $p'$ , such that fun is maximized at  $P=0$  or  $P=1$  where the machine is completely predictable, and fun is always negative in between. Thus, a person with these  $G$  and  $H$  preferences would not find slots fun.

Fig. 7 shows a case where  $H^- = H^+ = 1$  but  $G/G'=1/3$ , which means the player enjoys a unit of success at  $E'$  three times more than a unit of success at  $E$ . Here we see positive fun between  $P=0$  and  $P=0.2$ , with peak fun around  $P=0.05$ . Finally, Fig. 8 shows a player who has the same  $G/G'$  preference but who also has a good sense of slot humor ( $H^- = 0.5$  and  $H^+ = 1.0$ ). Here we see a broader and higher range of positive fun, with peak fun at about  $P=0.10$ .

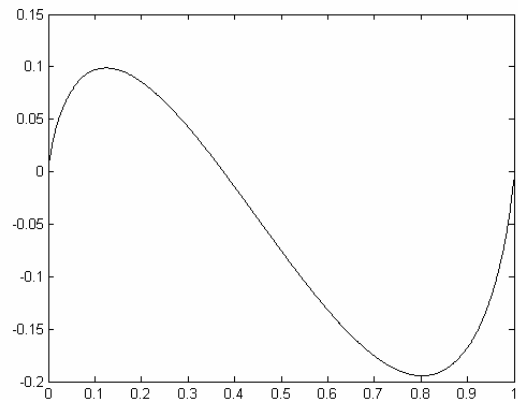


Fig. 8. A plot of the fun function  $f$ , where the scaling factors for  $E$  and  $E'$  are  $G/G'=1/3$ , for a player with a good sense of slot humor, showing that fun is positive for  $0 < P < 0.4$  and peaked at  $P=0.10$ .

These plots, which I call *Goldilocks functions*, are useful because they illustrate the basic tradeoff between  $E$  and  $E'$  via  $G$  and  $G'$ , and the relative importance of  $H^-$  and  $H^+$ , to fun in slots. That is, people would only play slots (as they do) if  $G < G'$ , which means that the fun in slots comes more from Explanations ( $E'$ ) that *resolve* Violations than from Expectations ( $E$ ) that *prevent* Violations in  $EVE'$ . Moreover, for players with  $G < G'$ , a player's sense of slot humor is also important, and players with  $H^- < H^+$  will find slots more fun. In short, it only makes sense to reduce  $E$  and incur  $V$  to achieve  $E'$  if the player enjoys a unit of  $E'$  more than he enjoys a unit of  $E$  – and this makes even more sense to a player with a good sense of slot humor.

### C. Limitation

One limitation of the above analysis is that it assumes the player's *mental models* for  $J$  and  $P=1/J$  reflect the  $J$  and  $P$  of the machine he plays. But in fact a player's models may be different, especially for  $P$ , since people are known to exhibit many biases in probabilistic inference and knowledge. For example, in the well-known bias called "gambler's fallacy", if a series of coin flips has come up with more heads than tails then the person will think he is "overdue" for tails, i.e., he thinks that the probability of tails on the next toss is  $>50\%$ . This raises the question of how such a bias in the player's model might affect fun, i.e., perhaps the fun comes from "wishful thinking" in a bias like the gambler's fallacy.

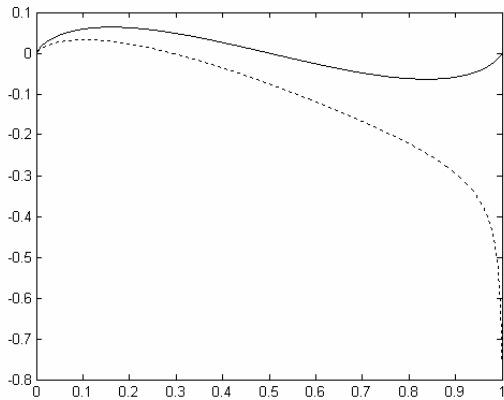


Fig. 9. A plot of  $E'$  for two cases. The dashed line applies to the case where the actual frequency  $F$  of a jackpot is less than the player's mental model  $P$ ,  $F=0.75*P$ . The solid line applies when  $F=P$ .

But here again, like the case of subjective utility discussed earlier (Section II.A), the bias does not explain fun in slots because it would make slots *less fun* not more fun. To see why, consider the following expression for  $E'$  where  $P$  reflects the player's model for the probability of a jackpot and  $F$  reflects the actual frequency of a jackpot from the machine:  $E' = -\{F * \log P - (1-F) * \log (1-P)\}$ . Assuming  $F=cP$  where  $c=0.75 < 1$ , Fig. 9 plots the result for  $E'$  (dotted line) compared to the baseline case (solid line) where  $c=1$ . The plot shows that fun is actually decreased by the bias.

### D. Validation

As one test of  $EVE'$ , the predicted  $P$  for peak fun in slots can be compared to the actual  $P$  of real slot games that people play for fun. As noted in Section II.A, a real slot machine offers a range of jackpots  $\{J_i\}$ , where each  $J_i$  has a  $P_i$  that is roughly proportional to  $1/J_i$ . Here, for a real machine, I consider the "Twenty-One Bell three-wheel nickel machine" analyzed by Scarne [11], who notes that the payback to players is 94% and who says, "I'd be playing it just for fun; I wouldn't expect to beat it in the long run."

Presumably this real machine has been optimized for fun, or at least it is close to peak fun for slot players. Scarne's detailed analysis shows that the set of payoffs  $\{J_i\}$  has  $i=8$  where  $P_i * J_i$  is roughly constant for all  $i$ . The average rate  $P$  of getting some payoff ( $i=1$  through 8) is computed to be 13%. This result compares well to the peak  $P$  of around 0.10-0.15 given by  $EVE'$ 's theory, as seen in Figures 3 and 8.

## III. EXTENSION

Section II showed that fun in slots can be seen as arising from informational play rather than financial play. That is, the aesthetic experience of slot fun can be seen as a net difference in information gained from good outcomes versus bad outcomes, where information gain is measured by marginal entropy.

Each instance of information gain (good or bad) is a *Violation* ( $V$ ) of *Expectation* ( $E$ ) that is resolved with either a pleasurable (good outcome) or displeasurable (bad outcome) *Explanation* ( $E'$ ) – and net fun comes when the marginal entropy of good outcomes given by  $-P * \log P$  is larger than the marginal entropy of bad outcomes given by  $-(1-P) * \log (1-P)$ .

But slots is a game of luck, and this raises the question of how  $EVE'$  might apply to games of skill. Here, to generalize, I consider any game of skill in which the player can score a win or loss. The player cannot control all aspects of the game, so the outcome is unknown. Thus, a player of this game can be modeled by a win probability  $S$ , which is like  $P$  in slot games because it establishes a player's Expectations for a win or loss on each attempt.

Following  $EVE'$  and focusing on the Violations ( $V$ ) and Explanations ( $E'$ ) that were seen to be the main source of fun in slots, the two possible outcomes in a game of skill are  $W$ =win or  $L$ =loss, which are akin to payoff  $J$  and payoff 0 in slots. Likewise, there are two kinds of Violations, namely: (i)  $V_L$ , when the player scores a loss, where the magnitude of Violation is  $V_L = -\log (1-S)$ , since  $\log (1-S)$  is the measure of Expectation for a loss, and (ii)  $V_W$ , when the player scores a win, where the magnitude of Violation is  $V_W = -\log S$ , since  $\log S$  is the measure of Expectation for a win.

Now the big difference between slot games and skill games is that a player's Explanation ( $E'$ ) for a Violation  $V_L$  in a game of skill will involve *causal logic* like, "I lost because I did  $x$  and I *might* have won if I did  $y$ ".

Per EVE' [3], such an Explanation would resolve *some* of the tension with *pleasure* where the amount of *some* would be proportional to the degree of *might* in the Explanation. In particular, if the Explanation was "... I *would* have won..." then the Explanation would resolve *all* the tension.

Here, as a simple and bounding case, I assume that such Explanations resolve all of the tension from  $V_L$  with *pleasure*. On the other hand, there can be no "what if" Explanation like this for a Violation  $V_W$  because the win *did* occur. That is, the only Explanation for  $V_W$  is "I won because I did x and I *should not* have won if I did x". Since this Explanation does not explain anything, I assume it resolves all of the tension from  $V_W$  with *displeasure*.

Thus, writing the equation for  $E' = E_L' - E_W'$  yields:

$$\begin{aligned} E' &= -\{(1-S) * \log(1-S) - S * \log S\} \\ &= \{S * \log S - (1-S) * \log(1-S)\} \end{aligned}$$

Notice that this equation is the same as that for slots (above), except negated because the Violations are opposite. That is, in slot games the win/loss Violations  $V_j/V_0$  are resolved with pleasure/displeasure because it is a game of luck, while in skill games the win/loss Violations  $V_w/V_l$  are resolved with displeasure/pleasure because it is a game of skill. In both cases a difference in marginal entropies is what gives rise to net fun, but the good/bad entropies are reversed because the goodness/badness of the information gain depends on the player's Explanation of the Violation. That is, the *amount* of information gain is measured in light of the player's mental models [10], which govern his *Expectations*, and the *impact* of this information is measured in light of the player's mental models, which govern his *Explanations*. In short, the player's *feelings of fun* depend on his *interpretation of the information* [3] via mental models [10].

Fig. 10 plots the function  $E'$  for this skill game, which is the inverse of Fig. 3 for the slot game. As seen in Fig. 10,  $E'$  is positive for  $P > 0.5$  and peak  $E'$  occurs at a  $P$  of about 0.85. Thus, it is most fun to win often but not always.

This analysis of skill games is admittedly speculative, but it does show how differences in Explanations of Violations for different games (e.g., luck versus skill) can give rise to different fun functions. It also shows how fun in skill games can be seen as arising from an information gain, much like that in slot games – and how the emotional impact of this information gain depends on the *mental models* that govern a player's *Explanations*, which in turn give rise to feelings of pleasure/displeasure.

In particular, the function  $E'$  versus  $S$  would be different for a game where the Explanations were of a different sort or sign (+ or -). For example, consider a game of skill where the player's *causal logic* is similar to the above in that Violations  $V_L$  are still resolved with pleasurable Explanations, but different from the above in that Violations  $V_W$  are *not resolved at all* rather than being resolved with displeasurable Explanations.

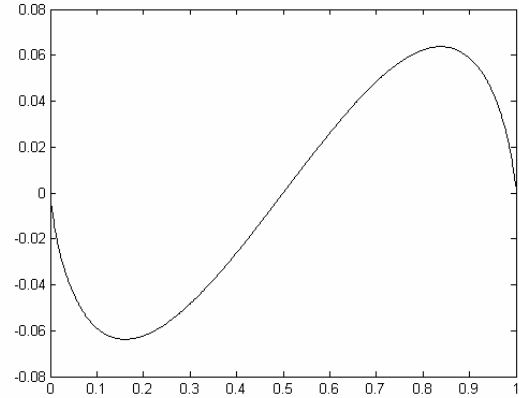


Fig. 10. A plot of the function  $E'$  versus win probability  $S$ , for a game of skill.  $E'$  is positive for  $S > 0.5$  and the peak  $E'$  is at about  $P = 0.85$ .

This might be the case if the player had a different *sense of humor* in the game, and/or if the player did not understand the game well enough to explain unexpected wins as something that *should not* have happened (see above). Here, retaining the assumption that a player always has an *excuse* (Explanation) for *losing*, and assuming that fun is dominated by  $E'$  rather than  $E$ , then fun would be driven by the following equation for  $E'$ :

$$E' = -(1-S) * \log(1-S)$$

which is simply the marginal entropy of the losing outcome. This Goldilocks function, plotted in Fig. 11, has the shape of an inverted bowl that is skewed towards large  $S$  and peaked at about  $S = 0.6$ .

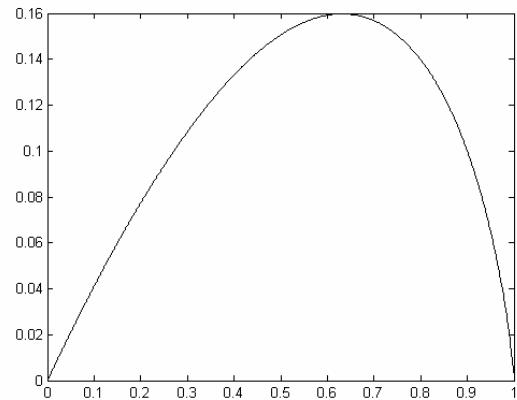


Fig. 11. A plot of  $E'$  versus win probability  $S$ , for a game of skill similar to Fig. 10 except with a different assumption about how the player resolves Violations  $V_W$  when he wins. Here the Goldilocks function for peak fun is broader and peaked at about  $S = 0.6$ .

As one point of empirical evidence, player's judgments of enjoyment (which I call *fun*) were measured in an experiment [12] using a variant of the game "Punch Out". This game is a simplistic simulation of a boxing match, where the player takes defensive actions and makes offensive attacks against a computer opponent, and each round is scored with a margin of victory ranging from -10 (worst loss) to +10 (best win). After each round the player gave a subjective rating of enjoyment, and the mean values were correlated to the margin of victory. The results showed that peak fun occurred at a margin  $m$  of +1; the peak fun dropped off rapidly for  $m < 1$  and dropped off less rapidly for  $m > 1$ ; fun was negative for  $m < -2$ ; fun was positive for  $m > -1$ .

Here, to compare EVE's theory to this data, a win probability  $S$  must be converted to a measure of margin  $m$ . Using the standard approach of a Rasch model [13], margin  $m$  would vary roughly as  $\text{logit}(S) = \log(S/(1-S))$ .

Now, besides  $E'$  per the above equation, the theory of EVE' includes  $E$  from the equation  $E = S * \log S + (1-S) * \log(1-S)$ . Also,  $E$  is scaled by a factor  $G$  and  $E'$  is scaled by a factor  $G'$ . Here I assume  $G/G' = 1/3$ , which is the same ratio used in the slot plot of Fig. 8. Fig. 12 plots the fun function,  $f = G * E + G' * E'$ , against  $\text{logit}(S)$ . Compared to the empirical data (discussed above), the theoretical results match the quantitative value of the margin ( $m = +1$ ) for peak fun as well as the qualitative drop-off of the curve, which is faster for  $m < 1$  (going negative) than for  $m > 1$  (staying positive).

This agreement between theory and data suggests that similar modeling with EVE' [3] can be used to explain and predict fun in other games, and that the nature of players' Explanations of Violations in "Punch Out" may be similar to those assumed in the above analysis.

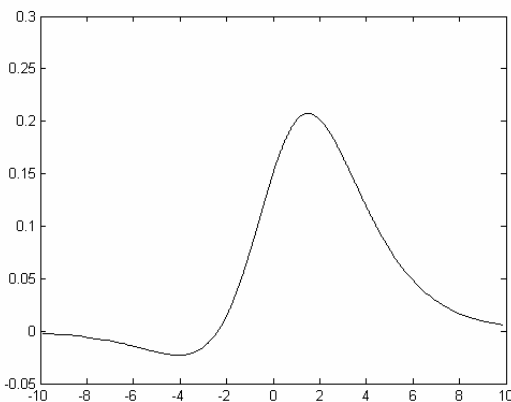


Fig. 12. A plot of the fun function  $f$  versus win margin  $m$ , where  $m$  is computed as  $\text{logit}(S)$  and  $S$  is the win probability. The function is the sum of fun from  $E$  and  $E'$ , weighted by  $G:G'$  factors in ratio of 1:3. The peak fun occurs at  $m = +1$  and fun drops off more rapidly for  $m < 1$  than for  $m > 1$ . This theoretical model matches empirical data on players' enjoyment in a game of "Punch Out" [12].

#### IV. CONCLUSION

The contribution of this paper is to show how fun in games can be analyzed with a computational-aesthetic approach, using Bayesian-information theory. In particular, I showed how slots and other games can be seen as informational games, played in a cognitive progression of Expectation-Violation-Explanation (EVE'), where fun arises from information gains that can be measured by marginal entropies. This finding is important because it provides a plausible explanation for human behavior in slot play, and because the same Bayesian-information theory of EVE' can be applied to other games and other aesthetic experiences in general – in order to model and measure how fun works.

The analysis was obviously simplified in not modeling the aesthetics of bells, wheels, coins, etc., and in assuming that the player's anticipations can be reduced to an average probability  $P$  of a payoff  $J$ . As such, the study does not capture all the nuances of each atomic E-V-E' experience in the "time domain". However, the results do capture major modes of time-averaged aesthetics in the "frequency domain", plotted as Goldilocks functions. These functions show how enjoyment can be modeled and measured by Bayesian extensions to Shannon entropies. The analysis is also limited by the assumption of scaling factors, but theoretical bounds on these factors are discussed (e.g.,  $G < G'$ ), and the results are seen to be relatively insensitive within the bounds.

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