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11-1-2021

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Technical Report: UTEP-CS-21-88

Recommended Citation

Reyes, Christopher and Kreinovich, Vladik, "Why Do People Become Addicted: Towards a Theoretical Explanation for Eyal's Experiment-Based Hook Model" (2021). *Departmental Technical Reports (CS)*. 1621.
https://scholarworks.utep.edu/cs_techrep/1621

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Why Do People Become Addicted: Towards a Theoretical Explanation for Eyal's Experiment-Based Hook Model

Christopher Reyes and Vladik Kreinovich

Abstract Why do people become addicted, e.g., to gambling? Experiments have shown that simple lotteries, in which we can win a small prize with a certain probability, and not addictive. However, if we add a second possibility – of having a large prize with a small probability – the lottery becomes highly addictive to many participants. In this paper, we provide a possible theoretical explanation for this empirical phenomenon.

1 Formulation of the Problem

Addiction: bad and not so bad. The word "addiction" has a negative connotation: people get addicted to gambling, to drugs, to alcohol, to smoking: they try it first, and then they feel the urge to continue the corresponding habit. However, from the psychological viewpoint, the same habit-forming can have (and often has) positive effects as well: people get addicted to healthy lifestyle, like eating healthy food and exercising regularly, people get addicted to their creative activities ranging from art and music to scientific research, people fall in love with each other – which is usually a good type of addiction.

For bad addiction, we need to understand where it comes from so we can prevent it and – if it already happened – cure it. For good addition, we also need to understand where it comes from, so that we can have more people living healthy lives, we can have more people exploring their creativity, etc. In both cases, it is important to understand where addiction comes from, i.e., how we form the resulting habits.

Eyal's experiments and the resulting Hook Model. Understanding can mean different things. We can discuss what physiological processes occur in the brain when

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a person becomes addicted. In the future, this may help us prevent the formation of bad habits and promote formation of good ones, but as of now, the results of such an analysis are somewhat far away from practical applications. In general, we are not yet able to use this knowledge to prevent or promote habit forming.

More practical results have reasonably recently come from a different study: an analysis of which situations cause addictions and which do not – without the physiological analysis of how exactly addiction is formed in the brain. Such studies have indeed been performed, they are describe in Nir Eyal's book; see [1] and references therein. Eyal's results can be best explained on the example of gambling addiction – since in gambling (as opposed to other bad addictions), rewards and risks can be clearly stated in objective numerical form.

Eyal started with a seemingly natural simple gambling model, in which a person gets:

- a reward r with some probability p, and
- no reward at all with the remaining probability $1-p$.

This can be a simplified model of playing a lottery, this can be a simplified version of playing the slot machine at a casino, etc. Somewhat surprisingly, this seemingly natural arrangement did not lead to any serious habit forming – participants played a little bit, but did not form a habit of playing.

The situation changed drastically when he introduced a somewhat more realistic description of a gambling situation, in which there are two levels of rewards:

- a very large reward R that happens with a very low probability p_ℓ, and
- a medium-size (actually, small) reward r that happens with a medium-size probability p_m.

For example, in a lottery where a lottery ticket costs 1 dollar, many people get a \$5 prize and very few get a very big, multi-million dollar prize. In simulated situations, a significant proportion of participants became addicted to playing this lottery: they eagerly participated in it again and again.

What we do in this paper. In this paper, we provide a natural explanation for this phenomenon: namely, we explain why lotteries with two levels of rewards are more addictive.

2 Analysis of the Problem and the Resulting Explanation

Naive picture of the situation. In order to understand the situation, let us start with the first – as it turns out, naive – description of the situation. In this (naive) picture, when people engage in some repeated financial arrangements, they expect to earn some money. This is why people invest money in stocks or place them in a savings account – this way they expect to gain more than they invested. This is true for investments, but can this explain why people play lotteries in the first place? As it turns out, not really.

Indeed, if a person plays the above-described simple lottery – in which we get a reward r with probability p – a large number of times N, then we get this reward in approximately $p \cdot N$ cases, so the overall reward is equal to $p \cdot N \cdot r$. To get this reward, the person needs to buy N lottery tickets. So, if we denote the price of a ticket by t, the person spends the amount $t \cdot N$.

In this picture, a person should play the lottery only if his/her expected gain is larger than his/her investment, i.e., if $p \cdot N \cdot r > t \cdot N$. But where can this extra money come from? The only possibility is for this money to come from the lottery organizers, but this does not make sense: why would the lottery organizers give away money? Lotteries usually earn money for the state, not lose them. So, this naive picture not only does not explain why people get addicted, it does not even explain why people play lotteries in the first place.

A similar conclusion can be made for any lottery i, in which we get:

- money reward r_{i1} with probability p_{i1},
- money reward r_{i2} with probability p_{i2}, etc.,

In this case, after N plays, we get:

- money reward r_{i1} approximately $N \cdot p_{i1}$ times,
- money reward r_{i2} approximately $N \cdot p_{i2}$ times, etc.

So, the overall reward is equal to

$$N \cdot p_{i1} \cdot r_{i1} + N \cdot p_{i2} \cdot r_{i2} + \ldots,$$

and the average reward per play is equal to

$$p_{i1} \cdot r_{i1} + p_{i2} \cdot r_{i2} + \ldots \tag{1}$$

Unless the lottery organizers give out money for free, this expected amount cannot be larger than the price of a lottery ticket. Thus, from this naive viewpoint, people should not play lotteries at all – but they do. Why?

A more adequate picture of the situation. Researchers have been analyzing human decision making for many decades. In particular, they analyzed a question of how a rational person should make decisions. Their conclusion (see, e.g., [2, 3, 5, 8, 9, 10, 11]) is that a rational person, when presented several situations i in which he/she will get:

- money reward r_{i1} with probability p_{i1},
- money reward r_{i2} with probability p_{i2}, etc.,

should select an alternative i for which the following expression is the largest possible:

$$u_i = p_{i1} \cdot u(r_{i1}) + p_{i2} \cdot u(r_{i2}) + \ldots, \tag{2}$$

for some function $u(r)$ (called *utility function*) describing this person's preferences.

This formula is similar to the above “naive” formula (1), the main difference is that instead of computing the expected value (1) of the monetary gain r_{ij}, we compute the expected value of the *utility* $u(r_{ij})$ of this gain – which, crudely speaking, describes the people “degree of happiness” upon receiving such gain.

That the degree of happiness is not directly proportion to the monetary amount makes sense. If it was, then every time you get an extra \$1, you would experience the same increase in happiness. In reality, however:

- if you have no money and someone gives you \$1, then you become very happy;
- on the other hand, if you already have \$100 and someone gives you \$1, then your degree of happiness does not change that much.

In other words, the perceived difference between having \$0 and \$1 is much higher than the perceived difference between having \$100 and \$101.

Empirical studies found that this aspect of human behavior can be reasonably well described if we use the square root utility function $u(r)=\sqrt{r}$; see, e.g., [4, 7]. In this case, indeed, the difference $u(101)-u(100)=\sqrt{101}-\sqrt{100}\approx 0.05$ is much smaller than the difference $u(1)-u(0)=\sqrt{1}-\sqrt{0}=1$.

In this approach, the person is willing to play a lottery in which he/she gains r_j with probability p_j, $j=1,2,\ldots$ if his/her expected utility

$$p_1\cdot\sqrt{r_1}+p_2\cdot\sqrt{r_2}+\ldots$$

is larger than the utility $\sqrt{t}$ corresponding to the ticket price t:

$$p_1\cdot\sqrt{r_1}+p_2\cdot\sqrt{r_2}+\ldots\geq\sqrt{t}. \tag{1}$$

This more adequate model still does not explain why people play lotteries. Indeed, as one can easily check, the function $f(x)=\sqrt{x}$ is strictly concave – since its second derivative is negative. Concaveness means that for all possible convex combinations $r=\sum\limits_{i=1}^{n} p_i\cdot r_i$, where $p_i\geq 0$ and $\sum\limits_{i=1}^{n} p_i=1$, we have

$$\sum_{i=1}^{n} p_i\cdot f(r_i)\leq f\left(\sum_{i=1}^{n} p_i\cdot r_i\right).$$

Strict concaveness means that unless one of the values p_i is equal to 1 and other to 0, we have a strict inequality:

$$\sum_{i=1}^{n} p_i\cdot f(r_i)< f\left(\sum_{i=1}^{n} p_i\cdot r_i\right).$$

In particular, for our case, when $f(r)=\sqrt{r}$ and when some probabilities are different from 0 and 1, we get

$$\sum_{i=1}^{n} p_i \cdot \sqrt{r_i} < \sqrt{\sum_{i=1}^{n} p_i \cdot r_i}. \tag{2}$$

As we have mentioned, the folks organizing the lottery are not willing to lose money, so the average gain must be smaller than or equal to the price t of the lottery ticket:

$$\sum_{i=1}^{n} p_i \cdot r_i \le t. \tag{3}$$

By taking square root of both sides of this inequality, we conclude that:

$$\sqrt{\sum_{i=1}^{n} p_i \cdot r_i} \le \sqrt{t}. \tag{4}$$

Combining (2) and (4), we conclude that

$$\sum_{i=1}^{n} p_i \cdot \sqrt{r_i} < \sqrt{t},$$

i.e., that the condition (1) is never satisfied – and thus, that rational people should not play lotteries.

How can we explain that they not only play lotteries once in a while, but that many folks even become addicted to playing them?

Let us use an even more adequate model. The fact that the above model does not always explain human behavior means that we need to consider an even more adequate model of human behavior – a model that would take into account some additional features of human behavior.

One possibility for providing such more adequate model comes from the fact that the above model (implicitly) assumes that people adequately estimate the probabilities of different events. In reality, people tend to overestimate small probabilities. This phenomenon is described, e.g., in [4]. In [6, 7], we provide a possible theoretical explanation for this phenomenon. Based on this explanation, provide a formula relating a subjective probability ps of an event – i.e., the values that people use to make decisions – and the actual probability p: $ps = \dfrac{2}{\pi} \cdot \arcsin(\sqrt{p})$. For small value p, this means $ps = c_p \cdot \sqrt{p}$ for some constant c_p.

Thus, when making decisions, people maximize the expression

$$\sum_{i=1}^{n} ps_i \cdot u(r_i) = c_p \cdot \sum_{i=1}^{n} \sqrt{p_i} \cdot \sqrt{r_i} = c_p \cdot \sum_{i=1}^{n} \sqrt{p_i \cdot r_i}.$$

So, they play the lottery if

$$c_p \cdot \sum_{i=1}^{n} \sqrt{p_i \cdot u_i} > c_p \cdot \sqrt{t},$$

i.e., equivalently, if

$$\sum_{i=1}^{n} \sqrt{p_i \cdot u_i} > \sqrt{t}. \tag{5}$$

For a simple lottery, this means that $\sqrt{p \cdot r} > \sqrt{t}$. Since for a simple lottery, we must have $p \cdot r \le t$ – otherwise the lottery organizers will be losing money – the inequality $\sqrt{p \cdot r} > \sqrt{t}$ is not possible.

This explains why simple lotteries are not addictive.

What about more complex lotteries. For an above-described more complex lottery, with two levels of rewards, when $p_\ell \cdot R + p_m \cdot r \approx t$, we have

$$(\sqrt{p_\ell \cdot R} + \sqrt{p_m \cdot r})^2 = p_\ell \cdot R + p_m \cdot r + 2\sqrt{(p_\ell \cdot R) \cdot (p_m \cdot r)} > t.$$

So, in this case, $\sqrt{p_\ell \cdot R} + \sqrt{p_m \cdot r} > \sqrt{t}$.

A similar inequality holds if we consider three or more different reward levels. This explains why more complex lotteries are addictive.

Acknowledgments

This work was supported in part by the National Science Foundation grants:

- 1623190 (A Model of Change for Preparing a New Generation for Professional Practice in Computer Science), and
- HRD-1834620 and HRD-2034030 (CAHSI Includes).

It was also supported by the AT&T Fellowship in Information Technology, and by the program of the development of the Scientific-Educational Mathematical Center of Volga Federal District No. 075-02-2020-1478.

The authors are thankful to all the participants of the 26th UTEP/NMSU Workshop on Mathematics, Computer Science, and Computational Science (El Paso, Texas, November 6, 2021) for valuable discussions.

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