Web3 Meets Behavioral Economics: An Example of Profitable Crypto Lottery Mechanism Design

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Abstract—We are often faced with the non-trivial task of designing incentive mechanisms in the era of Web3. As history has shown, many Web3 services failed mostly due to the lack of a rigorous incentive mechanism design based on token economics. However, traditional mechanism design, where there is an assumption that the users of services strategically make decisions so that their expected profits are maximized, often does not capture their real behavior well as it ignores humans’ psychological bias in making decisions under uncertainty. In this paper, we propose an incentive mechanism design for crypto-enabled services using behavioral economics. Specifically, we take an example of a crypto lottery game in this work and incorporate a seminal work of cumulative prospect theory into its lottery game mechanism (or rule) design. We designed four mechanisms and compared them in terms of utility, a metric of how appealing a mechanism is to participants, and a game operator’s expected profit. Our approach is generic and will be applicable to a wide range of crypto-based services where a decision has to be made under uncertainty.

Index Terms—Token economics, lottery game mechanism design, behavioral economics, cumulative prospect theory

I. INTRODUCTION

We are often faced with the non-trivial task of designing incentive mechanisms in the era of Web3. As history has shown, many cryptocurrencies failed mostly due to the lack of a rigorous incentive mechanism design based on token economics [1]. Mechanism design, a field of microeconomics and game theory, helps us derive an optimal mechanism where desired objectives are achieved by incentives. Desired objectives here mean that a service, an application, or a system works as intended by its operators. In this paper, we propose an incentive mechanism design for crypto-enabled services using behavioral economics. Behavioral economics combines elements of economics and psychology to understand how and why people behave the way they do in the real world. Cumulative prospect theory (CPT) is a seminal work of behavioral economics that captures humans’ bias in making decisions under risk [3]. We take an example of a crypto lottery game in this work and leverage CPT to design a profitable lottery game mechanism for a game operator. We design four mechanisms and compare them in terms of utility, a metric of how appealing a mechanism is for participants, and a game operator’s expected profit. We rigorously test possible parameters and functions of CPT to identify the conditions where the game is appealing to participants and profitable for the game operator.

II. MODEL

There are two entities, namely a game operator and participants. An operator first determines a lottery game rule. Given a rule, participants determine whether or not to join a game. We define our generic lottery game as follows. A participant needs to pay an entry fee $f$ to join a game. We assume that participants are ordered by their ranks at the end of a game. The $j$-th ranker will be given a prize $P_j$, and $P_1 \geq P_2 \geq \cdots \geq P_{N_p} \geq 0$ where $\sum_{j=1}^{N_p} P_j = P$. The source of prizes is collected entry fees. An operator of the game takes $r$ of the total amount of entry fees, say $r = 10\%$, for their revenue.

For an operator to predict if participants will join a game, a naive approach would be to calculate the expectation of their profit and check if it is positive, which is called expected utility theory (EUT). However, it is obviously unrealistic to assume that participants follow EUT as this implies that no one will join a game [2].

III. PROPOSED METHOD

We propose a method for an operator to be able to design a lottery game mechanism that takes into account participants’ behavioral bias. Again, the objectives of an operator and participants are both maximizing their profits. In this regard, an operator needs to determine a profitable mechanism, i.e., $P_j$ that gives an operator as well as participants more profits, and given a mechanism participants strategically determine whether or not to join a game under not EUT but CPT.

We compare the four mechanisms, namely, (i) Winner-Take-All, (ii) Top-$k$ (Linear weighting), (iii) Top-$k$ (Exponential weighting), and (iv) three bands, in this paper. Fig. 1 shows each’ prize distribution versus ranks. In this figure, $N_p = 100$ and $k = 20$ (20% of participants will receive prizes for the top-$k$ mechanisms). As can be seen from this figure, the top ranker will receive all prizes in the winner-take-all game, whereas the top 20 (or 50) out of 100 will share a prize based on their ranks in the top-$k$ and three-band mechanisms.
Similarly, when a game is designed such that participants receive prizes but small amounts, it is less appealing to them. We used Tversky and Kahneman’s value function $v(x)$ with $\alpha = 0.88, \lambda = 2.25$ and probability weighting function $w_{TK}(p)$ with $\delta = 0.65$ [3], $r = 10\%$, and $f = 1$. Right: Utility comparison under the different assumptions.

IV. PERFORMANCE EVALUATION

We compare the mechanisms described in the previous section in terms of participants’ utility under the CPT assumption. We also clarify how $r$ and $f$ affect the operator’s profit and how profitable each mechanism is. Regarding $f$, we assume cardinal values (e.g., 1, 2) rather than actual currencies for generality. A positive utility means that a mechanism is attractive to participants, and they thus should join, and vice versa. Furthermore, the higher utility, the more attractive to participants.

We determine the optimal $k$s for the two top-$k$ mechanisms (i.e., linear weighting and exponential weighting described) and use them for the overall comparison.

Fig. 2 shows average utilities over $N_p$ versus $k$. As can be seen from this figure, for both weighting methods, when $k$ is high (i.e., when most of the participants are expected to receive prizes but small amounts), it is less appealing to them. Similarly, when $k$ is extremely low (i.e., when only a few participants receive prizes), it is also less appealing. We can see from this figure that there are optimal points on both linear weighting ($k = 16\%$) and exponential weighting ($k = 6\%$). We use these $k$s for the following evaluation.

We clarify the relationships between utility and number of participants, $N_p$, as well as different assumptions (i.e., value and probability weighting functions, CPT versus EUT). As mentioned in the previous section, we compare (i) Tversky and Kahneman’s value function and (ii) Prelec’s (the same $v(x)$ and $w_{Prelec}(p)$ with $\alpha = 0.65, \beta = 1$) [4], where these parameters were inferred by their past social experiments (e.g., [3], [4]). We also assumed $r = 10\%$ and $f = 1$ and varied $N_p$ from 1 to 200. The optimal parameters of $k$ in the two top-$k$ mechanisms were used, namely $k = 16\%$ and $k = 6\%$ for linear and exponential weighting, respectively.

Fig. 2 shows the comparison of utilities by different mechanisms and assumptions. We can clearly see the difference in utilities under the CPT assumption. The top-16\% (linear weighting) is the most appealing mechanism for participants in the sense that (i) the minimum number of participants required to achieve a positive utility (i.e., 21 required for the top-16\% (linear weighting), 34 for the top-6\% (exponential weighting), 53 for the winner-take-all, and 97 for the three bands) and that (ii) it achieves higher utilities than the others. From this result, we can say that the winner-take-all and top-6\% (exponential weighting) are too risky and less appealing to participants and that the top-16\% (linear weighting) mechanism provides a good balance of risk and return.

V. CONCLUSIONS

We have proposed a method of designing the mechanism of lottery games with an example of a crypto-based lottery game. The key idea is to incorporate behavioral economics into mechanism design to better predict participants’ willingness to join a game and the operator’s profitability based on utility analysis. In particular, we leveraged CPT to model participants’ behavior. We proposed four mechanisms for the game and thoroughly evaluated them in terms of utility and profit by varying parameters. Our evaluation suggests that the top-$k$ (linear weighting), which distributes prizes to top-$k$ participants of a game and the amount of prizes linearly declines with their ranks, is the best mechanism among the four mechanisms.

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2 Although we proved that the expected utility of risk-neutral participants is always negative, we plot it for reference purposes.