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A Proposed Change to S&P 500 Oracle Incentive Mechanism

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Abstract

In this report, we propose a change to the incentive mechanism of Subnet 28 (S&P 500 Oracle) that will bring miner rewards in closer alignment with the goals of the subnet. We will show, through a series of simulations, that the proposed change will result in better distribution of miner rankings, stablize miner registration, and incentivize miner diversity.
Keywords: *bittensor, S&P 500*

1 Introduction

The Bittensor network is a decentralized, peer-to-peer network that aims to use collective intelligence to solve various computational problems. Individuals contribute data, compute, or intelligence (build models) and are rewarded according to the efficacy of their contributions. Subnet 28, S&P 500 Oracle, is one whose goal is to provide predictions of the S&P 500 index. To that end, the subnet's incentive mechanism must reward miners not only by the accuracy of their predictions, but by their utility as investment strategies. The current incentive mechanism is based on two components that are equally weighted:

1. Root Mean Squared Error (RMSE): How close to the true price did the model get?
2. Directional Accuracy: Did the model predict the correct direction of the price movement?

We propose to implement the following changes to the current components:

1. RMSE becomes "Δ factor": the absolute difference between predictions and actual S&P 500 price
2. Introduce a tiered ranking system for directional accuracy
3. Distribute rewards exponentially according to miner rank

The following simulations illustrate that the incentive mechanism changes noted above will better align miner rewards with model utility. In other terms, rewards will be more concentrated within top-performing miners while penalizing poor models. We will show throughout this report that these changes will provide much better alignment between a miner's rewards and their utility as an investment strategy.

2 Methods

2.1 Simulated Price Data

We built a ground-truth price dataset for our simulations using the statistics of the S&P 500 index. This process began by pulling recent data from Yahoo Finance, to get the current price (P) and the variance (Q) over the last 12 epochs (i.e. the 12 most recent 5-minute intervals). We then modeled the stock price as brownian motion with step size according to Q, where the price at time $t+1$ is pulled from a gaussian distribution centered around the price at time t with a variance of Q. The result was a dataset we could use to test changes to the framework of Subnet 28, the S&P 500 Oracle.

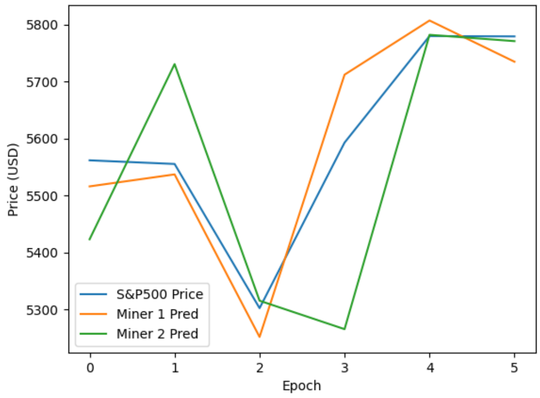

Figure 1: An example trial of the simulation. Two miners were selected, one good (Miner 1) and one bad (Miner 2), to demonstrate the raw results of the simulation.

2.2 Simulated Miners

We designed the population of miners to uniformly span the reasonable range of stock price prediction. To simulate the miner predictions, we applied a doubly stochastic modificiation to the ground truth data. We started with the ground truth data for time t described in the previous section (P_t). Noise was added to the price at time t by adding a random number X, drawn from distribution $\mathcal{N}$.

$$\mathcal{X} \sim \mathcal{N}(\mu, \sigma^2) \tag{1}$$

To methodically titrate the noise (to get a range of miner quality according), σ^2 was chosen to be monotonically increasing from $0.1Q$ *to* $2Q$ for each miner. We chose $0.1Q$ as the lower bound because the incentive mechanism normalizes according to the best model, and a perfect prediction model would be unreasonable. This distribution ensures $miner_m$ will, on average, have a smaller RMSE than $miner_{m+1...n}$. Another way to think about this is that $miner_n$ will make predictions that are 2x as volitile as the actual S&P 500, thus spanning the reasonable range of miner quality.

In addition to RMSE, we also added a random element for the directional accuracy. To do this, we assigned a probability to each miner (γ_m), again monotonically increasing from 0.1 *to* 0.9, indicating a given miner's directional error rate. In short, $miner_{m+1}$ has a higher probability of predicting the wrong direction than $miner_m$. The center of $\mathcal{X}$ (μ) was also pulled from a distribution (Equation 2).

$$\mu = \begin{cases} U(0,1) \leq \ \gamma_m : & -|\ \mathcal{N}(0,\, \sigma^2)\ | \\ U(0,1) > \gamma_m : & |\ \mathcal{N}(0,\, \sigma^2)\ | \end{cases} \tag{2}$$

For each trial, a random number $U(0,1)$ was drawn from a uniform distribution and compared to γ_m. The result of this comparison determines whether the model will be biased toward or against the correct direction. It is important to note that this only biases the miner towards the correct direction, and doesn't dictate it, allowing for reasonable expectations for directional accuracy in the context of predictions. This all results in the final prediction for $miner_m$ at time t being:

$$\rho_{m,t} = P_t + \mathcal{X}_{m,t}(\mu, \sigma^2) \tag{3}$$

See figure 1 for an example trial depicting how two of the miners may predict the S&P 500 price.

2.3 Miner Verification

Now that we have operationalized a population of miners that span the reasonable range of predictive quality, we must ensure that they behave as expected. We queried the miners over 100 epochs and found that the miners did follow the expected trends for directional accuracy (Figure 2A), and RMSE (Figure 2B) according to the old incentive mechanism.

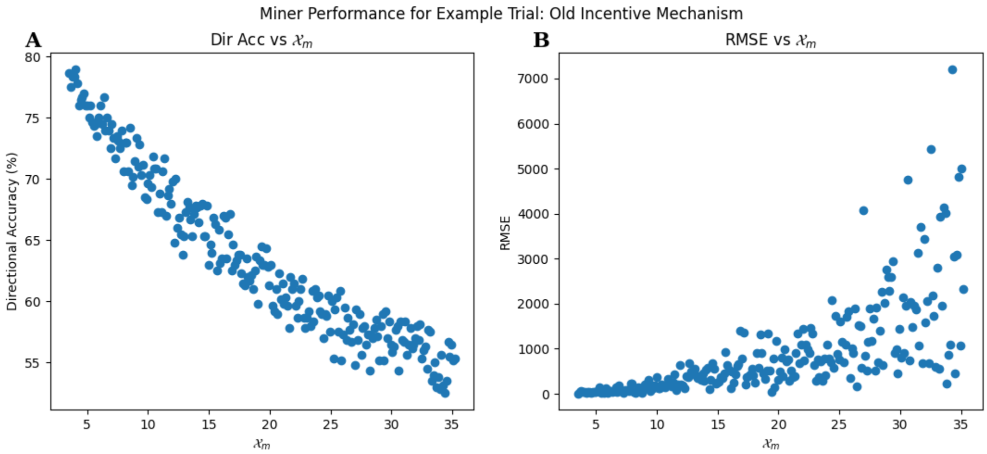

Figure 2: Simulated miners follow expected trends for both old incentive metrics. A.) Miners are roughly rank ordered by directional accuracy. B.) Miners are roughly rank ordered by RMSE.

2.4 New Incentive Mechanism

Δ Factor

The proposed Δ factor for $miner_m$ is calculated as the difference between miner predictions and the true S&P 500 stock price, shown in 4. This is a relatively small change, as Δ is highly related to the current RMSE-based incentive structure (Figure 3A), however, Δ is more interpretable since the units are in USD.

$$\Delta_m = \sum_{t=1}^{t=6} |\rho_{m,t} - P_t| \tag{4}$$

Directional Accuracy

Unlike investers, both RMSE and Δ factor are agnostic to the direction of the stock price, and therefore must be accounted for using directional accuracy. We firmly believe that the utility of Subnet 28 is directly tied to the the degree to which miner predictions can drive investment decisions. Therefore, miners who predict the correct direction of price movement should recieve higher incentives. With this philosophy in mind, we propose a tiered ranking system for miners first considering directional accuracy, then Δ.

Combined Ranking System

For each timepoint t, we sort miners into two buckets: one for miners with correct direction predictions and a second for miners with incorrect direction predictions. Once miner outputs are separated, we rank the miners within each bucket according to their Δ factor (Equation 4) for the epoch. Therefore, if a miner incorrectly predicts the direction of the S&P 500 price, the maximum rank is limited to one plus the number of miners that predicted correctly during that timepoint. We then calculate these rankings for each timepoint $(t-1, t-2, ...t-6)$ in the relevant prediction epoch. Therefore each timepoint t has 6 predictions (the prediction from 5 minutes ago, 10 minutes, etc. Up to 30 minutes). Then, the final ranks for this epoch is given by the average of their rankings across timepoints.

Rankings to Validator Weights

Once the miners have all been ranked, we convert these ranks to validator weights using equation 5.

$$W_m = e^{-0.05*rank_m} \tag{5}$$

The constant shown in equation 5, -0.05, is a hyperparameter which controls the steepness of the curve (i.e. what proportion of the emissions are allocated to rank 1, 2, 3,... etc.). We chose this value to fairly distribute across miners to mitigate the effect of rank volatility. For example, if a good miner

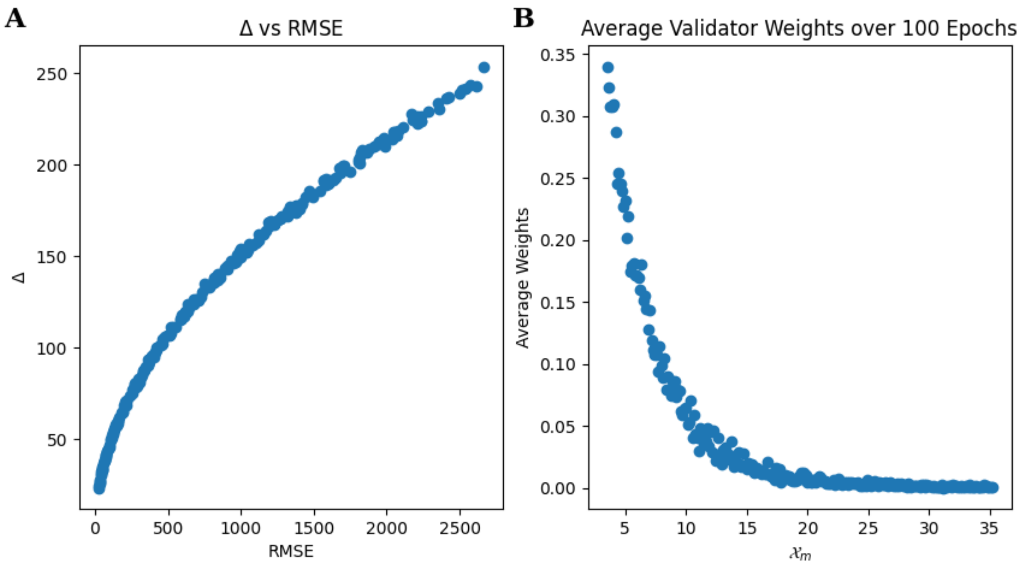

Figure 3: A.) The new Δ factor is highly related to the current RMSE incentive. This change is mostly cosmetic, in order for the units of error to be in USD. B.) Average validator weights over the 100 epochs plotted against $\mathcal{X}_m$. This shows the relationship between the quality of simulated miners' outputs (titrated through $\mathcal{X}_m$) and their respecitve weights.

makes bad predictions on one trial, they will still be rewarded and avoid deregistration. Once weights are calculated from equation 5, we take one final step before committing them. One criticism from Bittensor community members is that Subnet 28 (unintentionally) incentivizes owning UID slots, regardless of miner performance. To address this concern, we set weights for miners ranked 101+ to 0. This ties into the directional ranking system, as miners who randomly guess the direction will trend towards 50% accuracy. These miners will not be able to maintain a top 100 ranked position, and therefore receive no incentives. See figure 4A for a breakdown of the ranking-to-reward function. To summarize the rewards distribution, the top 10 miners recieve $\sim 40\%$ of the rewards, the following 40 miners (rank 11-50) recieve $\sim 50\%$, and the remaining $\sim 10\%$ goes to the next 50 miners (rank 51-100).

3 Results

3.1 New Incentive Mechanism

We will now dive into the expected behavior of the new incentive mechanism. The first and most important result is depicted in Figure 4. We show in pannel B, that the new incentive mechanism significantly increases the slope of validator weights, resulting in a wider spread of miner incentives. Good models will be rewarded more, while poor models will recieve little to no rewards. Additionally, miners are now indirectly rewarded for S&P 500 predictions, and instead directly rewarded for performance relative to other miners. This results in diminishing returns for good miners who want to register extra UIDs, thereby encouraging a diversity of models. We believe this new incentive mechanism will increase competition within the Subnet 28 ecosystem and motivate participants to improve their models rather than just reregistering UIDs.

4 Conclusion

In this paper, we proposed and evaluated changes to Subnet 28's incentive mechanism. We focused on aligning miner rewards with the goals of Subnet 28. Through extensive simulations, we demonstrated that replacing RMSE with the Δ factor and revising the calculation of directional accuracy led to

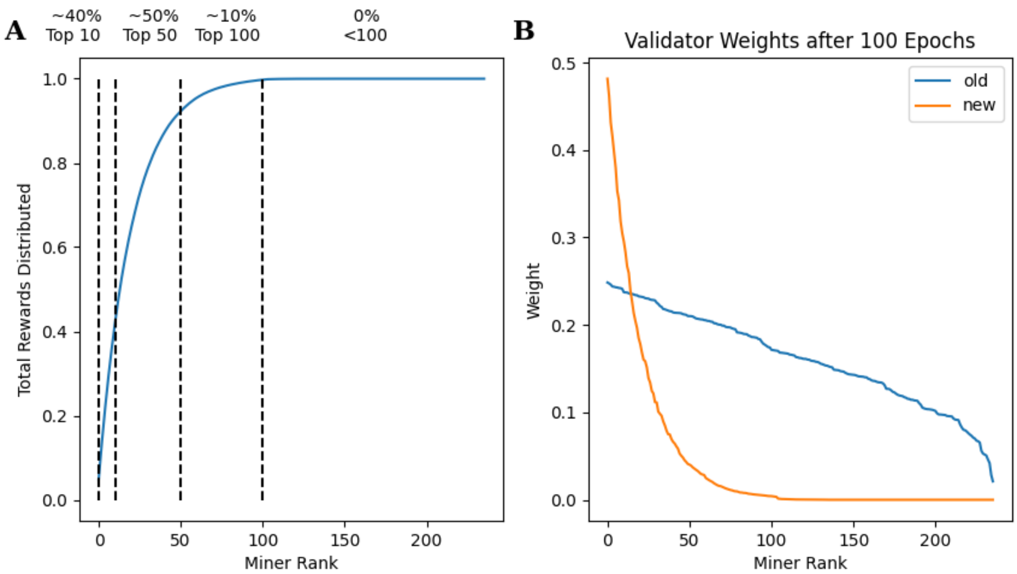

Figure 4: A.) Cumulative sum of validator weights sorted by miner rank. Each miner recieves more incentive than those ranked below them. This results in roughly 40% of rewards going to the top 10 miners, 50% to the next 40 miners, and the remaining 10% goes to miners ranked 51-100. B.) The proposed change in incentive mechanism will result in a steeper miner curve, better rewarding good models while discouraging simply grabbing uids.

significant improvements in miner performance distribution and stability. The new incentive mechanism increases interpretability and effectively differentiates high and low-quality miners, promoting fairer reward allocation. The new, tiered-ranking system also incentivizes model diversity and discourages registering multiple UIDs with the same model through diminishing returns. Foundry is committed to improving the performance, stability, and utility of the S&P 500 Oracle and the Bittensor ecosystem at large.

