A Proposed Change to snpOracles Incentive Mechanism

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Abstract

In this report, We propose a change to the incentive mechanism of subnet 28 (snpOracle) that will bring miner rewards in closer alignment with the goals of the network. We will show, through a series of simulations, that the proposed change will result in better distribution of miner rankings, stablize miner registration, and align miner rewards better with the network's goals.
Keywords: *bittensor, S&P500*

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&P500 oracle, is one whose goal is to provide accurate predictions of the S&P500 index. To that end, the 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?

Two simple changes are proposed to the current incentive mechanism:

1. RMSE to be replaced with Δ
2. Change to a tiered ranking system for directional accuracy

We will show throughout this report that these changes will provide much better alighment between miner rewards and utility as investment strategies.

2 Methods

2.1 Simulated Price Data

The ground truth price data for our simulations was built according to the statistics of the S&P 500 index. We started by pulling recent data from yfinance, in order 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.

2.2 Simulated Miners

The first population of miners was designed to uniformly span the reasonable range of stock price prediction. Miner predictions were simulated using a doubly stochastic modificiation to the ground truth data. We start first 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 $\mathcal{N}$.

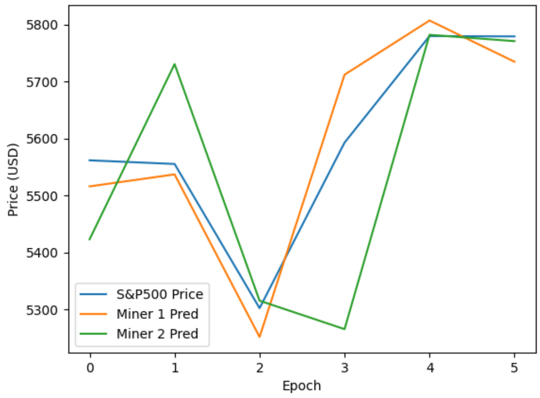

Figure 1: One example trial of the simulation using a uniform miner distribution. Two miners were selected (one good and one bad) to demonstrate the raw results of the simulation.

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

In order to titrate the noise (to get a range of miner quality according to RMSE), σ^2 was chosen to be monotonically increasing from $0.1Q$ *to* Q for each miner. We chose $0.1Q$ as the lower bound because the incentive mechanism normalizes according to the best model, and a perfect stock-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&P500, 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, which dictates that miners directional error rate. In short, $miner_{m+1}$ has a proportionately higher percent chance to predict the wrong direction than $miner_m$. The center of $\mathcal{X}$ (μ) was also pulled from a distribution (Equation 2).

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

On each trial, a random number $U(0,1)$ was drawn from a uniform distribution and compared to γ_m. This dictates wether 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$P500 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 in fact follow the expected trends for directional accuracy (Figure 2A), and RMSE (Figure 2B) according to the old incentive mechanism.

2.4 New Incentive Mechanism

RMSE

The new Δ factor for $miner_m$ is calculated as shown in equation 4. This change is a small one, as Δ is highly related to the current RMSE incentive (Figure 3A), but it allows people to better interpret

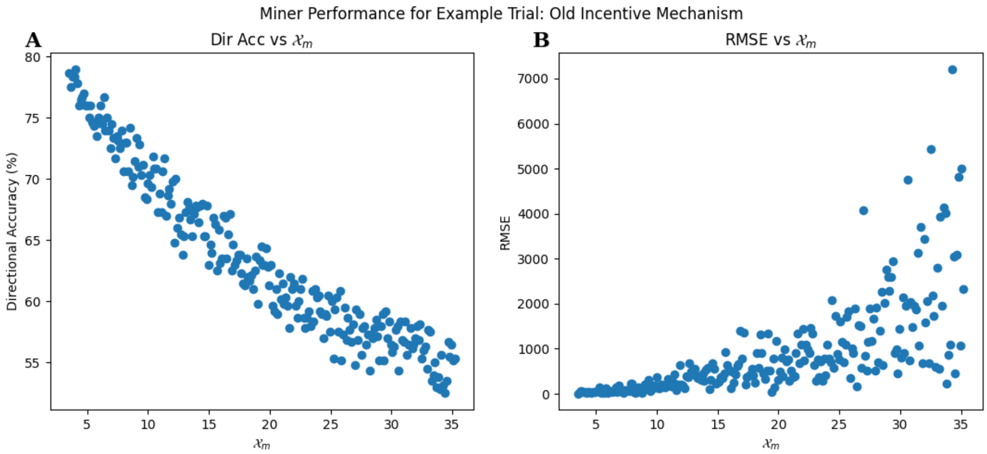

Figure 2: Simulated miners follow expected trends for both incentive metrics. A.) Miners are roughly rank ordered by directional accuracy. B.) Miners are roughly rank ordered by RMSE.

miner performace since the units are in USD.

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

Directional Accuracy

Due to both RMSE and Δ being agnostic to the direction of the stock price (unlike investors) directional accuracy is an important addition. We also firmly believe that the utility of this subnet is directly tied to the the degree to which miner predictions can drive profit in investment decisions. This means that miners who predict the correct direction of price movement should be rewarded more. Considering this phylosophy, we propose a tiered ranking system for miners using first directional accuracy, then Δ.

Combined Ranking System

For each timepoint t, we sort miners into two buckets: correct direction prediction and incorrect direction prediction. From there, we rank the miners in each bucket separately with Δ (Equation 4). Therefore, if a miner predicts the incorrect direction, the highest they can rank is one plus the number of miners that predicted correctly. 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 -0.05 is a hyperparameter that 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. If, for example, a good miner makes bad predictions on one trial, they will still be rewarded and likely not be deregistered. Once weights are calculated from equation 5, we take one final step before committing them. One complaint we have recieved is that subnet 28 (unintentionally) incentivizes owning UID slots, even if the miner model is sub-par. In order to address this, we set weights to miners ranked 101+ to 0. This ties in nicely with the directional ranking system, as randomly guessing direction will trend the miner towards 50% accuracy, meaning they will not be able to maintain a top 100 slot. For a breakdown of the ranking-to-reward function, see figure 4A. In short, the top 10 miners recieve 40% of the rewards, the following 40 miners (rank 11-50) recieve 50%, and the remaining 10% goes to the next 50 miners (rank 51-100).

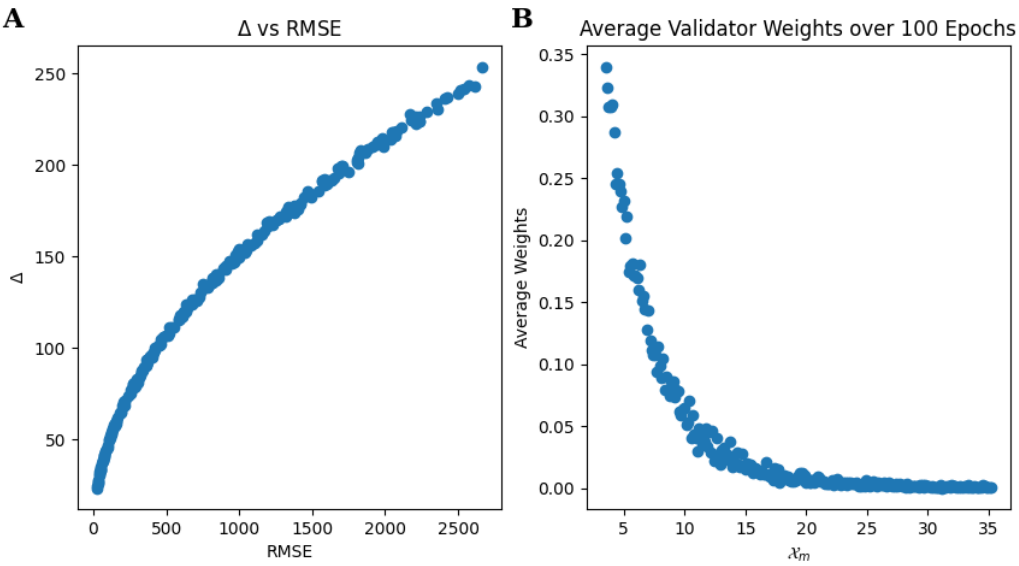

Figure 3: A.) The new Delta factor is highly related to the current RMSE incentive. This change is mostly cosmetic, in order for the units of error to be in USD. B.) Average validator weights over the 100 epochs plotted against $\mathcal{X}_m$
. This shows the relationship between our simulated miners'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

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 3. We show in pannel B, that the new mechanism demonstrates a stark increase slope for the validator weights, which results in a larger spread of miner incentives. This means that good models will be rewarded more, while poor models will recieve less Tao. The added benefit is that miners are only indirectly rewarded for S&P500 predictions, and instead directly rewarded for perforance relative to other miners. This change results in deminishing returns for good models registering extra UIDs, and instead encourages a diversity of models. We believe this new incentive mechanism will increase competition on the subnet, and motivate participants to improve their models rather than just reregistering UIDs.

4 Conclusion

In this paper, we proposed and evaluated changes to the subnet 28's incentive mechanism, focusing on better aligning miner rewards with network goals. Through extensive simulations, we demonstrated that replacing RMSE with the Δ factor and revising the calculation of directional accuracy led to significant improvements in miner performance distribution and stability. The new incentive mechanism increases interpretability and effectively differentiates between 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 deminishing returns. This change is the first of many coming to subnet 28, all with the goal of improving the network's performance, stability and utility.

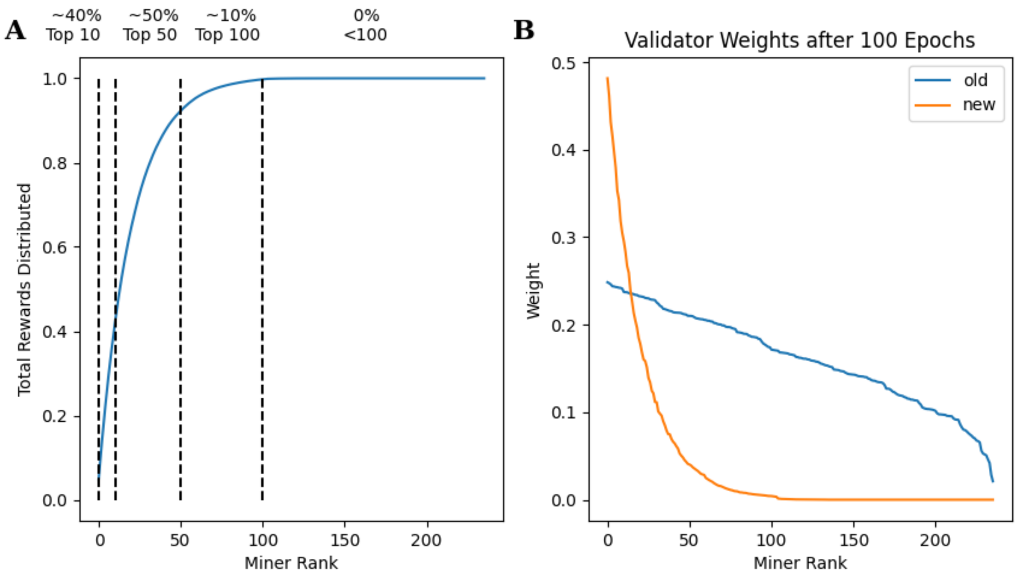

Figure 4: A.) The new Delta factor is highly related to the current RMSE incentive, meaning there will not be any appreciable change to current miner rankings, but with the added benefit of increased interpretability. B.) The proposed change in incentive mechanism will result in a steeper miner curve, better rewarding good models while discouraging simply grabbing uids.