Multi-Objective reward generalization: Improving performance of Deep Reinforcement Learning for selected applications in stock and cryptocurrency trading

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ABSTRACT
We investigate the potential of Multi-Objective, Deep Reinforcement Learning for stock and cryptocurrency trading. More specifically, we build on the generalized setting à la Fontaine and Friedman [6] (where the reward weighting mechanism is not specified a priori, but embedded in the learning process) by complementing it with computational speed-ups, and adding the cumulative reward’s discount factor to the learning process.

Firstly, we verify that the resulting Multi-Objective algorithm generalizes well, and we provide preliminary statistical evidence showing that its prediction is more stable than the corresponding Single-Objective strategies. Secondly, we show that the Multi-Objective algorithm has a clear edge over the corresponding Single-Objective strategy when the reward mechanism is sparse (i.e., when non-null feedback is infrequent over time). Finally, we discuss the generalization properties of the discount factor.

The entirety of our code is provided in open source format.

CCS CONCEPTS
• Computing methodologies → Reinforcement learning; Neural networks; Multi-task learning; • Applied computing → Economics.

KEYWORDS
Deep Reinforcement Learning, Multi-Objective Generalization, Multi-task learning, Stock Trading, Cryptocurrency Trading.

1 INTRODUCTION
Reinforcement Learning (RL) is a sub-field of Machine Learning specifically designed to handle learning processes for problems which involve a dynamic interaction with a given underlying environment. In a nutshell, a RL algorithm is supposed to learn to use the set of observable state variables s (describing the current state of the environment) to take the most appropriate admissible action a. Together with the environment’s intrinsic stochasticity, the state variables and action (s, a) determine the next state of the environment that the algorithm will visit. The algorithm’s ultimate goal is to maximise a cumulative reward (accounting for all actions taken in a given episode), which is in turn based on a pre-specified state–action reward function r (assigning a numerical reward r(s, a) to every pair (s, a) of given state and action undertaken). The algorithm uses several episodes (each accounting for an exploration of the environment, and each ending when a pre-specified end-state is reached) to train its action-making (by progressively updating the so-called Q-values [14] throughout the episodes). The reward function is both an integral part of the RL algorithm and the key metric against which its performance is measured.

An intuitive example of a set of problems which a machine may tackle using the RL framework naturally occurs in gaming. For instance, in the Atari 2600 games [10], the state of environment is represented by an image, the actions which the algorithm might take correspond to directional movements of the game’s characters, and rewards are cumulative game scores. Generally speaking, the vast majority of problems which the RL paradigm was — originally — applied to exhibit two clear features: firstly, (F1) they include robust and well-defined reward mechanisms (this provides the RL algorithms with the necessary quantitative feedback); secondly, (F2) they have a consistent, re-produceable and accessible environment. This allows the RL algorithms to thoroughly explore the environment in as many episodes as needed, and not to be affected by — potentially destabilizing — environment inconsistencies and abrupt variations in between episodes. Aside from the already mentioned field of gaming [10], RL techniques have been first deployed in the field of robotics [7], of personalized recommendations [15] and resource management [9].

The problems we are interested in, namely, those related to using RL for profitable, risk-reduced trading of financial tools based on historical data, only partially satisfy features F1 & F2. We detail this assertion by outlining three common problems in the field. Firstly, (P1) the reward mechanisms which one might use to judge the performance of a bot are not robust due the vast amount of noise coming from the financial environment. Secondly, (P2) the definition of the environment is often subjective, in the sense that one would need to decide which features are to be included in it

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We use a generalized with experience replay and target network stabilization given in [6], (this is in contrast to a videogame, where the structure of the environment is indisputable by design). Thirdly, (P3) the environment is technically not re-produceable, in the sense that only a single copy of any given time series is available for training. Despite these difficulties, a prolific literature is available, and one may get a sense of its range from the summary report [5].

1.1 Multi-Objective RL in finance

In this paper we exclusively focus on certain aspects related to problem P1. We investigate the advantages entailed by using the so-called Multi-Objective1 RL approach (in critic-only mode) to single-asset trading problems. Broadly speaking, Multi-Objective RL is a declination of RL devoted to learning in environments with vector-valued – rather than scalar – rewards. With methodologies including, among many, Pareto front-type analysis [16], dynamic multi-criteria average reward reinforcement learning [11], convex hull value iteration [2], and Hindsight Experience Replay techniques [1], the Multi-Objective RL paradigm is well-established in several non-finance related applications, see [12] for an expanded discussion; however, it appears to still be relatively under-explored2 in the context of financial markets.

In this context, the most commonly taken approach to Multi-Objective RL is to indirectly embed the desired multi-reward effects in parts of the model other than the reward mechanism itself (e.g., collaborating market agents [8]). Another – less investigated – approach is to consider an intrinsic Multi-Objective approach, but without generalization (i.e., the reward weights are set a priori, and do not part in the learning process). This is the case for the two reference works [3, 13], which we summarize in Section 2.

1.2 Our contribution

We use a generalized, intrinsically Multi-Objective RL strategy for stock and cryptocurrency trading. We implement this by considering extensions of Multi-Objective Deep Q-Learning RL algorithm with experience replay and target network stabilization given in [6], and deploying it on the Nifty50 stock index and BTCUSD trading pair.

1.2.1 Main Results. Our main findings are:

- Generalization. We show that our Multi-Objective RL algorithm generalizes well between four reward mechanisms (last logarithmic return, Sharpe ratio, average logarithmic return, and a sparse reward triggered by closing positions) for both the BTCUSD and NIFTY50 datasets.

- Stability on prediction. We use two metrics (Sharpe Ratio and cumulative profits) to show that the prediction of our Multi-Objective algorithm is more stable than the corresponding Single-Objective strategy’s.

- Advantage for sparse rewards. We show that the results of the Multi-Objective algorithm are significantly better than those of the corresponding Single-Objective algorithm in the case of sparse rewards3.

1.2.2 Structure of the paper. We summarize the main contributions of the reference works [3, 13] in Section 2. We provide the abstract setup of our proposed Algorithm in Section 3, and fill in the necessary quantitative details in Section 4. After spelling out the main technical features related to our code (see Section 5), we discuss our main results in Section 6. Final considerations and future outlook are given in Sections 7–8.

2 RELATED WORK

The reference works [3, 13] use multi-reward scalarization to improve on the following, well-established benchmark strategies in the context of price prediction of a single-asset: i) an actor-only, RL algorithm with total portfolio value as single reward, and ii) a standard Buy-and-Hold strategy. More specifically, the authors take as rewards the average and standard deviations from the classical definition of the Sharpe ratio, and combine them with pre-defined weights to favor risk-adjustment. In another variation, the resulting scalarized metric is modified to further penalize negative volatility.

The authors use a two-block LSTM neural network to directly map the last previously taken action (Buy/Sell/Hold) and the available state variables to the next action. The first LSTM block is used for high-level feature extraction, and the other one for reward-oriented decision making. From the experimental results the authors conclude superiority of their method over the two benchmarks in terms of cumulative profit and algorithm convergence, although an analysis of statistical significance is not provided 4.

While the scalarization approach is effective and highly intuitive, it nonetheless has the downside of having to a priori specify the balance of the individual rewards (via their weights). This introduces a human factor into the balancing of rewards, while the algorithm has the potential to generalize between many different weightings.

Driven by this, we choose not to scalarize the reward metrics, so that the weights can be changed also during the agent’s training (in fact, the weights are crucial part of the training). Additionally, a comparison with the results in [3, 13] is difficult, as the exact level of trading fees is not specified in these works.

To the very best of our knowledge, ours is first application of Multi-Reward RL in the sense of [6] to financial data.

3 ABSTRACT DEFINITION OF THE MODEL

We consider variations of the Deep-Q-Learning algorithm with Hindsight Experience Replay and target network stabilization [14] (DQN-HER) for both standard Single-reward or Multi-reward structure (in the sense of [6]) applied to single asset datasets.

3.1 The classical abstract setup

The basic structure of (DQN-HER) is concerned with maximizing cumulative rewards of the type

$$R_t = \sum_{i=t}^{T} \gamma^t r_i$$

(1)

1such an analysis is extremely tough, given that it is very hard to obtain statistically consistent positive returns in volatile single-asset problems
with discount factor $\gamma \in (0, 1)$. The algorithm fits a neural network taking the current state $s_t$ as input and giving an estimate of the maximum cumulative reward of type (1) achievable by subsequently taking each permitted action $a_t$. The learning process is linked to the Bellman’s equation update

$$[Q(s_t)]_{a_t} = (1 - \alpha)[Q(s_t)]_{a_t} + \alpha \left( r(s_t, a_t) + \gamma \max_{a_{t+1}} [Q(s_{t+1})]_{a_{t+1}} \right)$$  

for a given learning rate $\alpha \in (0, 1)$, and where $r(s_t, a_t)$ is the reward for taking action $a_t$ in state $s_t$.

### 3.1 Multi-Reward adaptation in the sense of [6].

#### 3.1.1 Multi-Reward adaptation in the sense of [6].

With respect to the previous case, the neural network’s input is augmented by a reward weight vector $w$, which is used to compute the total reward $w \cdot r(s_t, a_t)$ (here $r$ is the vector of rewards, and $\cdot$ denotes the standard scalar product). The Single-Reward case can be seen as a declination of the Multi-Reward case with constant suitable one-hot encodings vectors $w$. The (DQN-HER) algorithm is summarized in Algorithm 1 for the reader’s convenience.

### 3.2 Our abstract setup

The methodology we adopt in this paper is summarized in Algorithm 2, which directly stems from the underlying basic Algorithm 1. For the sake of clarity, Algorithm 2 highlights only the differences between the two algorithms. These modifications are related to:

i) a ‘random access point’ procedure: an episode uses a subset of the full price history of the training set, where the starting point is randomly sampled and the length is fixed.

ii) the generalization of the discount factor $\gamma$ as suggested in [6] (further augmenting the neural network’s input from $(s, w)$ to $(s, w, \gamma)$), and

iii) the specific choice of normalization spelled out in Subsection 3.2.1 below.

#### 3.2.1 Choice of Normalization.

We choose to indirectly normalize the neural network’s output variables (i.e., the approximate Q-values) by rescaling the rewards in the Bellman’s update (2). More precisely, whenever a minibatch

$$(s_i, y_i, w_i, r(s_i, a_i), a_i, s_{i,new}) \in \mathcal{B} \subset \{1, \ldots, \#\mathcal{R}\}$$

is randomly sampled from the replay $\mathcal{R}$ (see Algorithm 2, line 22), the rescaled vectors

$$\hat{r}(s_i, a_i) = \frac{\sum_{i \in \mathcal{B}} r(s_i, a_i)}{\|w_i\|^2}, \quad i \in \mathcal{B}$$

and associated scalar rewards $\{w_i \cdot \hat{r}(s_i, a_i)\}_{i \in \mathcal{B}}$ are fed to the training in place of the original sets $\{r(s_i, a_i)\}_{i \in \mathcal{B}}$ and $\{w_i \cdot r(s_i, a_i)\}_{i \in \mathcal{B}}$. Here, the matrix $\Sigma$ denotes the approximate covariance matrix computed using the reward vectors from the entire replay, namely

$$\Sigma = \text{Cov} \left( \{r(s_i, a_i)\}_{i \in \{1, \ldots, \#\mathcal{R}\}} \right).$$

With this choice, the overall scalar rewards $\{w_i \cdot \hat{r}(s_i, a_i)\}_{i \in \mathcal{B}}$ are normalized, in the sense that

$$\text{Cov} \left( \{w_i \cdot \hat{r}(s_i, a_i)\}_{i \in \mathcal{B}} \right) = 1.$$  

### 4 SPECIFIC DETAILS OF OUR MODEL

After having laid out the general structure of our RL setup (see Algorithm 2), we give precise substance to all quantities involved.

#### 4.1 State variables $s_t$

We define the state variables $s_t$ as the vector comprising both the current position in the market $p_t$ (whose precise details are given in Subsection 4.2 below) and a fixed lookback of length $t$ over the most recent log returns of close prices $\{z_t\}$: more explicitly, we set

$$s_t := \left( \begin{array}{c} \ln z_t - \ln z_{t-1} \\ln z_t - \ln z_{t-1} \\ln z_t - \ln z_{t-1} \\end{array} \right) \in \mathbb{R}^t \times \mathbb{R}.$$  

#### 4.2 Admissable Actions and Positions

As far as actions are concerned, we analyse two scenarios:

- Only Long Positions (LP): the agent is only allowed to perform two actions (Buy/Hold)$^5$, and consequently only switch between trading positions Long/Neutral.
- Long and Short Positions (L&S): the agent is allowed to perform three actions (Buy/Sell/Hold), and consequently switch between trading positions Long/Short/Neutral.

#### 4.3 Rewards and Profit

For a given single-asset dataset with close prices $\{z_t\}$, we define the logarithmic (portfolio) return at time $t$ as

$$\ell r_t := \begin{cases} \ln z_t - \ln z_{t-1}, & \text{if } \text{Long at time } t - 1, \\ - \ln (z_t - \ln z_{t-1}), & \text{if } \text{Short at time } t - 1, \\ 0, & \text{if } \text{Neutral at time } t - 1. \end{cases}$$

Let $L \in \mathbb{N}$ be fixed. We focus on three well-established rewards (at a reference given point in time $t$), namely:

i) the last logarithmic return (LR), which is nothing but (6);

ii) the average logarithmic return (ALR), given by

$$\text{ALR} := \text{mean} \left( \{ \ell r_s \}_{s=t-(L-1)}^t \right);$$

iii) the non-annualized Sharp Ratio (SR), given by

$$\text{SR} := \frac{\text{mean} \left( \{ \ell r_s \}_{s=t-(L-1)}^t \right)}{\text{std} \left( \{ \ell r_s \}_{s=t-(L-1)}^t \right)},$$

as well as the sparse, less conventional reward:

iv) a ‘profit-only-when-(position)-closed’ (POWC) reward, defined as

$$\text{POWC} := \begin{cases} \ln z_t - \ln z_{t_{LT}}, & \text{if Long closed at time } t - 1, \\ - \ln (z_t - \ln z_{t_{LT}}), & \text{if Short closed at time } t - 1, \\ 0, & \text{otherwise}, \end{cases}$$

where $t_{LT}$ is the time of last trade (i.e., last position change).

$^5$selling previously acquired assets
We substantiate all necessary components involved in the simulations of our model (given in Algorithm 2).

### 5 EXPERIMENTS

We substantiate all necessary components involved in the simulations of our model (given in Algorithm 2).

#### 5.1 Codebase

For the structure of our code, we took some inspiration from two open source repositories: the stocks environment at

https://github.com/AminHP/gym-anytrading

and the minimal Deep Q-Learning implementation at

https://github.com/mswang12/minDQN.

#### 5.2 Datasets

We focus our attention on two real datasets, namely

- **hourly**-data points for the BTCUSD trading pair (August 2017–June 2020), and
- **minute**-data points for the NIFTY50 stock index (March–June 2020).

Such data is shown in Figure 1. We notice the mostly downward trend (respectively, **strongly** upward trend) on the BTCUSD (NIFTY50) evaluation set.

![Figure 1: Close prices for train (white), evaluation (green), and test set (blue). Top (Bottom): BTCUSD (NIFTY50)](image)

4.3.1 **A note regarding trading fees.** In the interest of having an as clear as possible comparison of Single and Multi-reward algorithm performances (this is the main focus of this work), we choose not to include buy or sell fees when calculating rewards and profits, as this would add an additional intermediate layer for us to assess.

#### Algorithm 1 (DQN-HER)

| **Input:** | MultiReward ∈ {True, False} |
|**Parameters:** | toler ∈ (0, 1), batchsize, k, M ∈ Z, S ⊂ {1, ...}, M |
|**Output:** | Trained Multi-Reward agent. |

1. Take one-hot encoding vector w.
2. Initialize network \( Q: (s, w) \mapsto [Q_1(s, w), \ldots, Q_p(s, w)] \) mapping state variables \( s \) and weight vector \( w \) to expected discounted return of every action \( a \in \{1, \ldots, P\} \).
3. for \( i = 1, \ldots, M \) do
   4. Reset training environment.
   5. while episode i not finished do
      6. if MultiReward is True then
         7. Sample random reward weights \( w \).
      8. else
         9. Pick \( a \leftarrow \arg \max_a Q(s, w) \).
      10. end if
      11. if \( \text{Unif}(0, 1) < \text{tol} \) then
         12. Choose random action \( a \).
      13. else
         14. Conduct one step (get to new state \( s_{new} \)).
      15. end if
      16. Get associated reward \( w \cdot r(s, a) \).
      17. Append single experience (\( s, w, r(s, a), a, s_{new} \)) to experience replay \( \mathcal{R} \).
      18. if MultiReward is True then
         19. Add other \( k \) experiences to Replay by re-running lines 7-14-15-16 \( k \) times.
      20. end if
      21. if \( i \in S \) then
         22. Randomly sample batchsize units from \( \mathcal{R} \).
      23. end if
      24. end while

#### Algorithm 2 (DQN-HER) with discount factor generalization and random access point

1. Initialize network \( Q: (s, w, y) \mapsto [Q_1(s, w, y), \ldots, Q_p(s, w, y)] \) mapping state variables \( s \), weight vector \( w \), and discount factor \( y \) to expected discounted return of every action \( a \in \{1, \ldots, P\} \).
2. Randomly select subset of training set, and reset associated environment.
3. Sample random reward weights \( w \) and discount factor \( y \).
4. Pick \( a \leftarrow \arg \max_a Q(s, w, y) \).
5. Append single experience (\( s, y, w, w \cdot r(s, a), a, s_{new} \)) to experience replay \( \mathcal{R} \).
6. Randomly sample batchsize units from \( \mathcal{R} \), and normalize sampled \( Q \)-values according to Subsection 3.2.1.

5.1.1 **Open source directory and reproducibility.** Our entire code is provided in open source format (together with the necessary datasets) at

https://github.com/trality/fire.

In particular, the instructions for reproducibility are contained in the README.md file therein.
In all cases, we choose to work on datasets of 25,000 time points. We find this dataset length to provide a reasonable compromise between experiment running times, and significance of predictions. Moreover, in the interest of increasing the statistical significance of our experiments (see Subsection 6.4 below), we include an evaluation set in addition to train/test sets. The percentages of the data associated with training/evaluation/test sets are 64%–16%–20%.

5.3 Quantities of interest and benchmarks
All our considerations will be based on the following – quite standard – quantities:

- Total Reward: the cumulative reward over the considered portion of the dataset.
- Total Profit: the cumulative gain/loss obtained by buying or selling with all the available capital at every trade.
- Sharpe Ratio: the average return per step, divided by the standard deviation of all returns.

Crucially, results of Multi and Single-rewards simulations are compared against each other, as well as – individually – also against a basic Buy-and-Hold strategy.

5.4 Measures for code efficiency

5.4.1 Basic measures. The most important measures taken in this regard are as follows. Firstly, as we are primarily interested in assessing the potential superiority of a Multi-Reward approach over a Single-Reward one (and not to squeeze out the most out of a specific model), we decide to stick to a simple Multi Layer Perceptron (MLP) Neural Network (Algorithm 1 - line 2). Secondly, for the purpose of checking the performance in between training, we run the currently available model on full training and evaluation sets only for an evenly distributed subspace of episodes.

5.4.2 Random access point. As already anticipated, in each episode, we perform the training on a random, contiguous subset of the full training set with pre-specified length. While it introduces some noise in the training process, this method helps towards reducing overfit and, also, does not affect the overall relevance of the results.

5.4.3 Vectorized computation of Q-values. With the exception of the trading position \( p_t \), the time evolution of the state variables vector given in (5) is otherwise entirely predictable (as prices \( z_t \) obviously do not change in between training episodes). This implies that, given a predetermined set of \( n \) actions, the algorithm can efficiently vectorize the evaluation of the neural network for each separate trading position, and then deploy the results to speedily compute the associated \( n \) future steps. This method is feasible as the cardinality of admissible values of non-predictable state variables (i.e., the trading position) is low (three at most, in the L&SP case).

6 RESULTS
The results arising from several Multi and Single-Reward experiments (using Algorithm 2) on both BTCUSD and NIFTY50 datasets gave us four general indications, which we now discuss in detail in as many dedicated subsections.

6.1 Multi-Reward generalization properties
The first crucial conclusion that we can comfortably jump to is that the Multi-Reward strategy generalizes well over all different rewards. This can be seen on pretty much all plots in the Subsections 6.2–6.4 which compare Multi- and Single-Reward (these plots will also be used to support narrower and more specific considerations). Especially in Figures 8 & 9, where the Single-Reward is the same as the performance metric, it can be seen that the Multi-Reward strategy still generalizes. The training saturation levels may vary with those of the corresponding Single-Reward simulations, although this is likely caused by an apparent regularization effect of the Multi-Reward setting. As far as predictive power is concerned, the Multi-Reward method is – at the very least – not worse than its Single-Reward counterpart.

We move on to detailing more specialized results.

6.2 Multi-Reward improvement on strongly position-dependent rewards
Let us consider a trading reward which

i) is strongly dependent on a specific trading position, and
ii) is ‘sparse’ (meaning that it might take several time steps for such reward to return a non-zero value).

Intuition says that it is highly likely that the Single-reward RL algorithm will struggle to learn based on such a reward. On the other hand, it is expected that a Multi-Reward algorithm will perform better, due to the influence of easier rewards with different but similar goals. Furthermore, the performance difference between Multi and Single-case is expected to be even more pronounced when there are fewer trading positions allowed (thus further restricting the Single-case capabilities to learn).

Below, we confirm these intuitions for the POWC reward – which satisfies i) and ii) above – by running the Multi-Reward RL code with all four rewards considered in Subsection 4.3 in its dictionary.

6.2.1 Case LP. When opening Short positions is not allowed, the POWC reward provides a non-zero feedback only when Long positions are closed. This extremely sparse feedback is likely to be the justification of the poor training performance in Figures 2 and 4, where Single-Reward saturates the training at a much lower level than Multi-Reward. In contrast, the training for the Multi-case algorithm is much more consistent, as it can benefit from rewards with similar goals as POWC, but with more frequent feedback (e.g., LR). In the Multi-Reward case, the prediction performance exceeds the Buy-and-Hold threshold on the BTCUSD dataset in a more consistent and stable way than in the training saturation regime of the Single-Reward case. Furthermore, the average Long positions (which show the time of capital exposure to the market) are lower, which means less riks is taken and are also relatively stable (the difference in strategy between Multi and Single-Reward algorithm can be inferred by the different convergence of Long Positions).

6.2.2 Case L&SP. As expected, the difference between Multi and Single case is much narrower in this case, as Short positions can now be opened, see Figures 3 and 5. With the exception of the training saturation, relevant differences are not noted.
6.3 Random discount factor generalization

We have run several simulations with both fixed and randomly sampled discount factor (as was originally suggested in [6]) on both BTCUSD and NIFTY50 datasets. The results are consistent across all simulations: therefore, we only show the results for the BTCUSD dataset in Figures 6 and 7 (Multi-Reward case only, for reward SR...
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in both the LP and L&SP cases), as they are representative of all the remaining simulations.

We were able to notice the following general trends:

- **Generalization.** A graphical comparison of performance indicators suggests that the algorithm generalizes with respect to the value of the random discount factor.
- **Training saturation levels.** There is a visible difference of saturation levels, with the random discount factor version saturating at a consistently lower level than its non-random discount factor counterpart. It is plausible that the discount factor generalization serves the purpose of a neural network regularizer. The difference is more pronounced case L&SP .
- **Evaluation set saturation levels and average positions.** No significant differences are noticeable between the two cases.

Taking everything into account, our simulations point in the direction of validating the discount factor generalization assumption provided in [6]. Nevertheless, more extensive testing is necessary in order to fully confirm this.

Figure 6: Reward Performances, SR/LP/BTCUSD. Left (Right): Non-random (Random) discount factor

6.4 Consistent indications for predictability

Although a full statistical justification of the obtained results is beyond the scope of this paper, we nonetheless have achieved indications that validate the effectiveness and robustness of the Multi-Reward approach. We further detail this statement.

6.4.1 Consistent performance with respect to the Buy-and-Hold strategy. In the majority of simulations, the Multi-Reward is capable of – on average – improving over the Buy-and-Hold strategy benchmark (in terms of Sharpe ratio), on the evaluation (Figures 2, 8, 9) and, more importantly, on the test set (Figures 10–12). In the Nifty50 case, the agent comes close to the Buy-and-Hold threshold on the evaluation set (see Figure 9), which is more difficult to beat due to the strong upward trend (see Figure 1).

6.4.2 Comparing performance on training, evaluation, test sets. A commonly used model selection strategy is to pick the best performing model on the evaluation set. In Figures 10–12, the performance of such best performing model is shown (for training, evaluation, test) as it progresses through the episodes. We observe that the performance on the evaluation set (in terms of the Sharpe Ratio) is consistently good. In particular, the performance of the Multi-Reward model is at least as good as that of the Single-Reward model, while also being much more stable.

Furthermore, the profits on the test sets are higher and more consistent in the Multi-Reward case (especially in the case of NIFTY50, see Figure 12). The results in Figures 10–12 also show that the performance on the test set is loosely correlated with the one on evaluation set. This could be due to the noisiness of the learning process, and a neat difference between evaluation and test set. In any case, the performance on the evaluation is a reliable indication for the improved stability, as it depends on the stability of the learning process.

7 further work will be needed in future work to account for the exact impact of intrinsic RL noise
Figure 8: Reward Performances, SR/L&SP/BTCUSD, regularized agent’s network

Figure 9: Reward Performances, ALR/L&SP/NIFTY50, regularized agent’s network

Figure 10: Top (Bottom): Best model for profits (performance for training/evaluation/test set based on SR), BTCUSD

Figure 11: Top (Bottom): Best model for profits (performance for training/evaluation/test set based on ALR), BTCUSD

7 CONCLUSIONS

Firstly, we have validated the generalization properties of a Multi-Reward, Reinforcement Learning code with Hindsight Experience
Firstly, while the Multi-Reward approach can, in some cases, stabilize/improve results of some rewards using the other ones, it is not clear exactly how the rewards are influenced by each other (normalizations different from 3 could be investigated). Secondly, it would be interesting to conduct a more thorough research into different lengths and non-uniform sampling mechanisms for the experience replay (see [4]). Thirdly, a more thorough analysis on the use of a random discount factor should be conducted. Fourthly, one might perform a sensitivity analysis on more hyper-parameters. Fifthly, a more in depth analysis of the prediction power to provide statistical evidence is still needed. Sixthly, to ensure real-world performance, the impact of including trading fees has to be investigated. Finally, it would be interesting to further address the noisy convergence of the performance metrics (see Section 7.1).

7.1 Limits of the RL setting

The obtained results are, in nearly all occasions, subject to noise: more specifically, relevant performance indicators occasionally oscillate around – rather than approach – their limiting value (with respect to the number of epochs). This behaviour is consistent with what can be expected from a critic-only Reinforcement Learning approach. Additionally, despite the (not at all short) length of training, evaluation, and test set, the data is obviously correlated in time, thus the effectiveness of Reinforcement Learning is reduced.

8 FUTURE OUTLOOK

While we have highlighted some of the benefits that a Multi-Reward approach has over a Single-Reward approach for predictive properties of a critic-only RL paradigm for single-asset financial data, many questions remain partially answered, or even wide open.

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