# Trader-Company Method: A Metaheuristic for Interpretable Stock Price Prediction (AAMAS 2021)

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April 19, 2023

# Team

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We are team **Gamers**. We are Avyukta M.V., D. Sri Anvith, Darshana S. and Nemani Harshavardhan.

# Introduction

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2. Despite the abundance of big data, quantitative analysts face challenges in developing new rules. However, a reliable and widely accepted practical method to fully utilize these data is currently lacking.
3. Mainly due to the following 2 challenges:

# Challenges

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1. Efficient Market Hypothesis: states that a trader can never do consistently better than the market since the market (in an efficient scenario) corrects itself in response to the latest information. Real markets are almost efficient, and hence, hard to have a single explanatory model.
2. In the short term, stocks are still predictable to a certain extent and explainable by simple mathematical formulae called alpha factors. Although individual formulas are weak classifiers, combining these can lead to a more robust signal, similar to ensemble methods.

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1. Interpretability of models is also a challenge. Even with the best possible trading strategies, the predictive accuracies are limited, unsustainable, and uncertain.
2. In such highly uncertain environments, the interpretability of the model is of utmost importance as well. Historically, Investors have preferred linear factor models to explain asset prices, and Machine learning models are often underused due to their lack of interpretability. Using a combination of simple formulae can open up a possibility of interpretable machine learning-based strategies.

# PROBLEM

Our problem is forecasting future stock returns based on historical observations. Let $X_i[t]$ be the price of stock $i$ at time $t$, where $1 \leq i \leq S$ is the index of given stocks and $0 \leq t \leq T$ is the time index. Throughout this paper, we consider the logarithmic returns of stock prices as input features of models. That is, we denote the one period ahead return of stock $i$ by

$$r_i[t] := \log\left(X_i[t]/X_i[t-1]\right) \approx \frac{X_i[t] - X_i[t-1]}{X_i[t-1]}.$$

We denote returns over multiple periods and returns over multiple periods and multiple stocks by

$$\boldsymbol{r}_i[u:v] = (r_i[u], \cdots, r_i[v]), r_{i:j}[u:v] = \left(r_i[u:v], \cdots, r_j[u:v]\right)$$

# Problem

The Predictor sequentially observes the returns $r_i[t] (1 \leq i \leq S)$ at every time $0 \leq t \leq T$. For each time $t$, the predictor predicts the one-period-ahead return $r_i[t+1]$ based on the past $t$ returns $r_{1:S}[0:t]$. That is, the predictor's output can be written as

$$\hat{r}_i[t+1] = f_t(\boldsymbol{r}_{1:S}[0:t])$$

for some function $f_t$ that does not depend on the values of $\boldsymbol{r}_{1:S}[t:T]$.

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4. We can formalize this to:

   $$C_i(t) = \sum_{t \in T} sign(\hat{r}_i(t+1)) \times \hat{r}_i(t+1)$$

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2. Trader predicts returns based on simple mathematical formulae using interpretable alpha factors. Traders act as weak learners that help in the company's eventual predictions.
3. Company is a collection of traders. It updates the collection of traders by hiring well-performing traders and dismissing poorly-performing traders.

# Traders Simple Prediction

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2. Let $M$ be the number of terms in the prediction formula. For each $1 \leq j \leq M$, we define $P_j, Q_j$ as the indices of the stock to use, $D_j, F_j$ as the delay parameters, $O_j$ as the binary operator, $A_j$ as the activation function, and $w_j$ as the weight of the $j$-th term. Then, the Trader predicts the return value $r_i[t+1]$ at time $t+1$ by the formula

$$f_\Theta(\boldsymbol{r}_{1:S}[0:t]) = \sum_{j=1}^{M} w_j A_j \left( O_j \left( r_{P_j}\left[t - D_j\right], r_{Q_j}\left[t - F_j\right] \right) \right).$$

   where $\Theta$ is the parameters of the Trader:

$$\Theta := \left\{ M, \{P_j, Q_j, D_j, F_j, O_j, A_j, w_j\}_{j=1}^{M} \right\}.$$

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3. Ideally, we want to optimize the Traders by maximizing the cumulative returns:

$$\Theta^* \quad \arg\max_{\Theta} \sum_{u} \text{sign}\left(f_{\Theta}\left(\boldsymbol{r}_{1:S}[0:u]\right)\right) \cdot r_i[u+1]$$
$$:= \arg\max_{\Theta} R\left(f_{\Theta}, \boldsymbol{r}_{1:S}[0:t], r_i[0:t+1]\right)$$

but since this is a complex optimization, we introduce a novel evolutionary algorithm driven by Company models.

# Companies Optimization and Aggregation

This happens in 3 steps.

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3. Prune and Generate Traders

# PREDICTIONS

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Basically, each Traders predictions are gathered and aggregated given stock returns before t and outputs returns at day t.(from Trader-company Method: A Metaheuristic for Interpretable Stock Price Prediction)

**Algorithm 1** Prediction algorithm of Company

**Input:** $r_{1:S}[0:t]$:stock returns before $t$, Traders :$\{\Theta_n\}_{n=1}^{N}$
**Output:** $\hat{r}_i[t+1]$: predicted return of stock $i$ at $t$

**function** COMPANYPREDICTION
  **for** $n = 1, \cdots, N$ **do**
    $P_n \Leftarrow f_{\Theta_n}(r_{1:S}[0:t])$ ▷ Prediction by Trader (5)
  **end for**
  **return** Aggregate$(P_1, \cdots, P_N)$ ▷ Aggregation
**end function**

# Education

Here Traders belonging to the bottom Q percentile get their weights updated by the least squares method.(from Trader-company Method: A Metaheuristic for Interpretable Stock Price Prediction

**Algorithm 2** Educate algorithm of Company

**Input:** $r_{1:S}[0:t]$:stock returns before $t$
**Input:** Traders. $N$ : the number of Traders. $Q$: ratio.
**Output:** Traders

```
function CompanyEducate
    R_n ⇐ R(f_{Θ_n}, r_{1:S}[0 : t], r_i[0 : t + 1])    ▷ Trader's return (6)
    R* ⇐ bottom Q percentile of {R_n}
    for n ∈ {m | R_m ≤ R*} do                          ▷ for all bad traders
        Update w_i in (5) by least squares method
    end for
return Traders
end function
```

# Prune and Generate

Algorithm: (from Trader-company Method: A Metaheuristic for Interpretable Stock Price Prediction )

**Algorithm 3** Prune-and-Generate algorithm of Company

**Input:** $\boldsymbol{r}_{1:S}[0:t]$:stock returns before $t$, F: # of fit times
**Input:** $N$: the number of Predictors. $Q$: ratio.
**Output:** $N'$ Predictors

1: $\Theta_n \sim$ Unifrom Distribution
2: **for** $k = 1, \cdots, F$ **do**
3: $\quad R_n \Leftarrow R(f_\Theta, \boldsymbol{r}_{1:S}[0:t], r_i[0:t+1])$ ▷ Trader's return (6)
4: $\quad R^* \Leftarrow$ bottom $Q$-percentile of $\{R_n\}$
5: $\quad \{\Theta_j\}_j \Leftarrow \{\Theta_n | R_n \geq R^*\}$ ▷ Pruning
6: $\quad \{\Theta_j\}_{j=1}^{N'} \sim$ GM fitted to $\{\Theta_j\}_j$ * ▷ Generation
7: **end for**
8: **return** $N'$ Predictors with $\{\Theta_j\}_{j=1}^{N'}$

* If the parameter is an integer, we round it off.

# EXPERIMENTS

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1. Datasets: 2 real market datasets, S&P 500 and LSE which have one of the highest trading volumes and capitalizations, were used. Daily data from May 19, 2000, to May 19, 2020, for the S&P 500 and hourly data of 77 stocks from Sept 7, 2016, to Sept 7, 2019, from the LSE.

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2. Evaluation Protocols: 2 practical constraints, time windows and execution lags, are introduced to account for the locality in data and time taken to process inputs.
3. Metrics Used: Different metrics like Accuracy, Annualized returns, and Sharpe and Calmar ratio were used to evaluate the performances of prediction algorithms.

# Baseline Methods

The present system has been compared with baseline methods like

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5. State Frequency Memory RNN: a deep-learning-based stock price prediction algorithm incorporating Fourier transform into LSTM.
6. Symbolic Regression by Genetic Programming: prediction algorithm using genetic programming.

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Some ablation studies were also conducted with variations like

1. Using only Linear activation functions and Unary operators.

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1. Using only Linear activation functions and Unary operators.
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4. Gaussian vs. Gaussian Mixture for sampling in Generate step
5. Using MSE for educating and pruning instead of Cumulative results

# Performance

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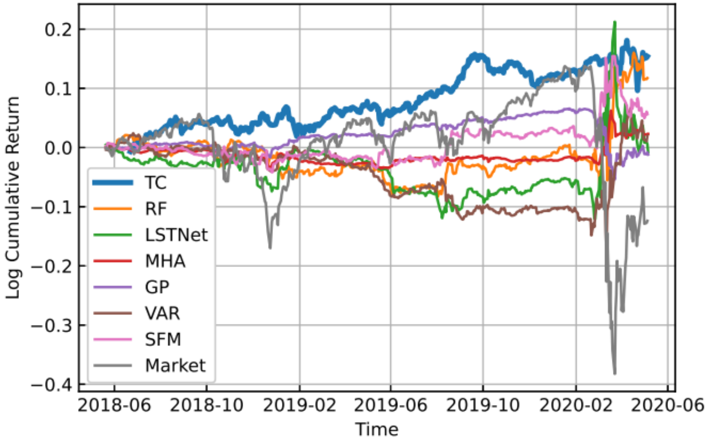

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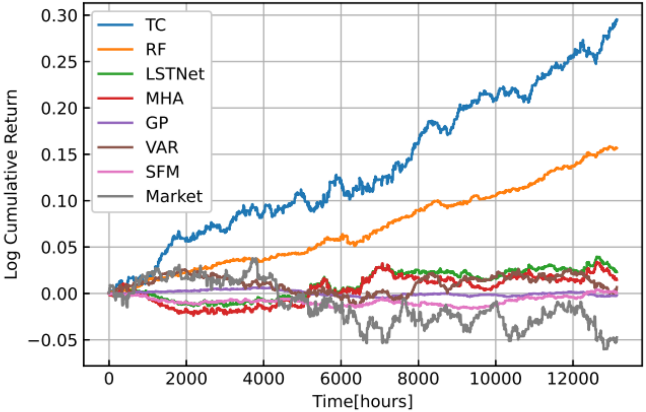
**Figure 2: Cumulative returns on US market**



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2. For US Markets, data pre-May 2018 was used for training and the rest for testing. For UK Markets, the first 1.5 years were used to train the model and the other half to test.

# Performance

Table 3: Performance comparison on US markets

| | ACC(%) | AR(%) | SR | CR |
|---|---|---|---|---|
| **Market** | 55.09 | -5.45 | -0.2 | -0.12 |
| **VAR** | 49.86 | 3.51 | 0.28 | 0.24 |
| **MHA** | 48.16 ± 1.1 | 0.66 ± 0.54 | 0.12 ± 0.10 | 0.11 ± 0.09 |
| **LSTNet** | 47.51 ± 1.12 | 3.61 ± 2.09 | 0.18 ± 0.10 | 0.16 ± 0.1 |
| **SFM** | 50.14 ± 1.09 | 5.95 ± 1.16 | 0.52 ± 0.10 | 0.50 ± 0.18 |
| **GP** | 54.99 ± 1.15 | -0.27 ± 0.67 | -0.03 ± 0.10 | -0.02 ± 0.08 |
| **RF** | 53.74 ± 1.11 | 4.38 ± 1.60 | 0.28 ± 0.11 | 0.25 ± 0.13 |
| **TC linear** | 53.23 ± 1.18 | 2.81 ± 0.36 | 0.86 ± 0.10 | 0.93 ± 0.28 |
| **TC unary** | 51.14 ± 1.17 | 1.50 ± 0.33 | 0.46 ± 0.11 | 0.44 ± 0.17 |
| **TC w/o educate** | 52.36 ± 1.15 | 3.69 ± 0.32 | 1.12 ± 0.10 | 1.36 ± 0.38 |
| **TC w/o prune** | 50.31 ± 1.14 | 1.08 ± 0.33 | 0.34 ± 0.11 | 0.30 ± 0.13 |
| **TC unimodal** | 50.33 ± 1.17 | 0.08 ± 0.35 | 0.02 ± 0.11 | 0.02 ± 0.08 |
| **TC MSE** | 51.35 ± 1.19 | 1.56 ± 0.54 | 0.30 ± 0.11 | 0.26 ± 0.13 |
| **TC (Proposed)** | **55.68 ± 1.16** | **10.72 ± 0.86** | **1.32 ± 0.11** | **1.57 ± 0.44** |

# Performance

Table 4: Performance comparison on UK markets

| | ACC(%) | AR(%) | R/R | CR |
|---|---|---|---|---|
| **Market** | 50.009 | -3.34 | -0.177 | -0.076 |
| **VAR** | 49.965 | 0.54 | 0.064 | 0.031 |
| **MHA** | 49.943 ± 0.991 | 1.01 ± 2.91 | 0.04 ± 0.15 | 0.03 ± 0.05 |
| **LSTNet** | 49.997 ± 1.007 | 1.53 ± 3.29 | 0.07 ± 0.18 | 0.05 ± 0.08 |
| **SFM** | 50.472 ± 8.810 | 0.23 ± 4.23 | 0.00 ± 0.22 | 0.02 ± 0.10 |
| **GP** | 50.017 ± 2.128 | -0.09 ± 1.47 | -0.02 ± 0.36 | 0.05 ± 0.12 |
| **RF** | 50.719 ± 1.177 | 10.45 ± 1.98 | 1.23 ± 0.23 | 1.17 ± 0.56 |
| **TC** | **50.928 ± 1.115** | **32.32 ± 1.04** | **2.23 ± 0.07** | **3.32 ± 0.44** |

# Performance Inferences

## Importance of Traders

Most traders make good predictions due to binary operators. This reduces the overall model complexity without losing expressive power. Using unary operators greatly deteriorates the model performance.Nonlinear activation functions also seem to improve performance.

# Performance Inferences

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### Importance of Combining Multiple Formulae

Genetic Programming generates a single formula, but the performance deteriorates over time due to the near efficiency of the Markets. Trader-Company model maintaining multiple formulae performed well over the test period.

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4. Using Multimodal distribution in the generation step also increases the performance substantially in comparison to the Unimodal distribution.

# Performance Inferences

### Comparison to other non-linear predictors

Other non-linear models, like MHA, LSTNet, and SFM, performed poorly except SFM, which was good for the US markets but not for the UK markets, while the Trader-Company Model consistently outperformed in both markets.

# Online Predictions

Instead of splitting data into training and testing, Sequential prediction setting has also been used. The models are sequentially updated every year where all the past observations were used for training.

# Performance Sequential

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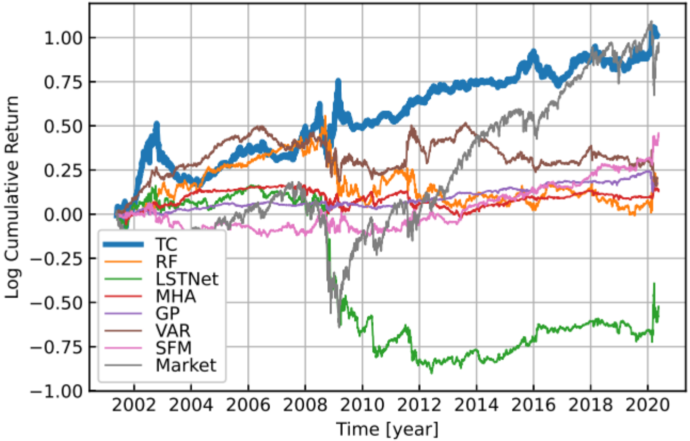

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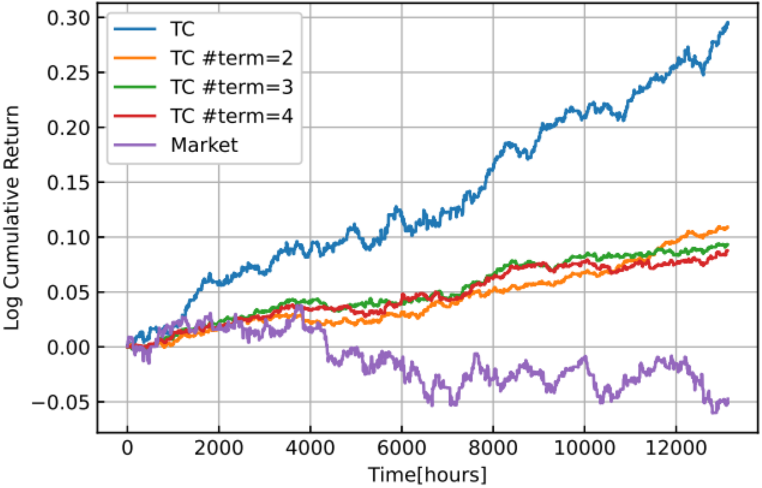

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5. Since each trader is represented by a mathematical formula, (which is trained and honed), real life finance experts could use these fomaulae and get insights into the nature of the market.
6. Since these formulae are very simple in nature (often consisting of *max*, *min*, *compare* etc.) we find that it is very easy to find a suitable interpretation of these formulae.

# RELATED WORK

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4. This is a new and exciting field, but it is still held that the unpredictable and volatile nature of the stock market cannot be modelled by neural networks.
5. As of now, simple regression methods work better than the complex neural network based methods.
6. This can perhaps be justified by the short time period prediction.

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3. In ensemble methods, some techniques such as pruning and random generation of experts have shown to be effective in various situations.
4. We would like to stress that, as we demonstrated in Section 4, the designs of pruning and generation schemes are crucially important in financial time series prediction.

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4. A algorithm to train and prune the traders by the company based on the overall revenue is given.

# Summary

1. The paper proposes a novel prediction method for financial time series
2. The setup consists of 2 main components - Traders and Company.
3. The traders use simple mathematical formulae ($\alpha$ factors) to make decisions.
4. A algorithm to train and prune the traders by the company based on the overall revenue is given.
5. The proposed algorithm has been applied on the US and UK stock markets and has been shown far outperform baseline methods.

# The End

Questions? Comments?