Efficient Integration of Multi-Order Dynamics and Internal Dynamics in Stock Movement Prediction

Thanh Trung Huynh
Ecole Polytechnique Federale de Lausanne, Switzerland

Minh Hieu Nguyen
Hanoi University of Science and Technology, Vietnam

Thanh Tam Nguyen*
Griffith University, Australia

Phi Le Nguyen
Hanoi University of Science and Technology, Vietnam

Matthias Weidlich
Humboldt-Universität zu Berlin, Germany

Quoc Viet Hung Nguyen
Griffith University, Australia

Karl Aberer
Ecole Polytechnique Federale de Lausanne, Switzerland

ABSTRACT

Advances in deep neural network (DNN) architectures have enabled new prediction techniques for stock market data. Unlike other multivariate time-series data, stock markets show two unique characteristics: (i) *multi-order dynamics*, as stock prices are affected by strong non-pairwise correlations (e.g., within the same industry); and (ii) *internal dynamics*, as each individual stock shows some particular behaviour. Recent DNN-based methods capture multi-order dynamics using hypergraphs, but rely on the Fourier basis in the convolution, which is both inefficient and ineffective. In addition, they largely ignore internal dynamics by adopting the same model for each stock, which implies a severe information loss.

In this paper, we propose a framework for stock movement prediction to overcome the above issues. Specifically, the framework includes temporal generative filters that implement a memory-based mechanism onto an LSTM network in an attempt to learn individual patterns per stock. Moreover, we employ hypergraph attentions to capture the non-pairwise correlations. Here, using the wavelet basis instead of the Fourier basis, enables us to simplify the message passing and focus on the localized convolution. Experiments with US market data over six years show that our framework outperforms state-of-the-art methods in terms of profit and stability. Our source code and data are available at https://github.com/thanhtrunghuynh93/estimate.

CCS CONCEPTS

• **Computing methodologies** → **Neural networks**;

KEYWORDS

hypergraph embedding, stock market, temporal generative filters

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*Corresponding author.

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1 INTRODUCTION

The stock market denotes a financial ecosystem where the stock shares that represents the ownership of businesses are held and traded among the investors, with a market capitalization of more than 93.7$ trillion globally at the end of 2020 [48]. In recent years, approaches for automated trading emerged that are driven by artificial intelligence (AI) models. They continuously analyze the market behaviour and predict the short-term trends in stock prices. While these methods struggle to understand the complex rationales behind such trends (e.g., macroeconomic factors, crowd behaviour, and companies' intrinsic values), they have been shown to yield accurate predictions. Moreover, they track market changes in real-time, by observing massive volumes of trading data and indicators, and hence, enable quick responses to events, such as a market crash. Also, they are relatively robust against emotional effects (greed, fear) that tend to influence human traders [36].

Stock market analysis has received much attention in the past. Early work relies on handcrafted features, a.k.a technical indicators, to model the stock movement. For example, RIMA [37], a popular time-series statistics model, may be applied to moving averages of stock prices to derive price predictions [3]. However, handcrafted features tend to lag behind the actual price movements. Therefore, recent approaches adopt deep learning to model the market based on historic data. Specifically, recurrent neural networks (RNN) [7] have been employed to learn temporal patterns from the historic data and, based thereon, efficiently derive short-term price predictions using regression [25] or classification [53].

However, stock market analysis based on deep learning faces two important requirements. First, multi-order dynamics of stock movements need to be incorporated. Price movements are often correlated within a specific group of stocks, e.g., companies of the same industry sector that are affected by the same government policies, laws, and tax rates. For instance, as shown in Fig. 1, in early 2022, prices for US technology stocks (APPL (Apple), META (Facebook), GOOG (Google), NFLX (Netflix)) went down due to the

general economic trend (inflation, increased interest rates), whereas stocks in the energy sector, like MPC, OKE, or OXY, experienced upward trends due to oil shortages caused by the Russia-Ukraine war. Second, the internal dynamics per stock need to be incorporated. In practice, even when considering highly correlated stocks, there is commonly still some individual behaviour. For example, in Fig. 1, APPL and GOOG stocks decrease less severely than META and NFLX, as the former companies (Apple, Google) maintain a wider and more sustainable portfolio compared to the latter two (Facebook, Netflix) [26].

Existing work provides only limited support for these requirements. First, to incorporate multi-order dynamics of stock markets, RNNs can be combined with graph neural networks (GNNs) [18]. Here, state-of-the-art solutions adopt hypergraphs, in which an edge captures the correlation of multiple stocks [40, 41]. Yet, these approaches rely on the Fourier basis in the convolution, which implies costly matrix operations and does not maintain the localization well. This raises the question of how to achieve an efficient and effective convolution process for hypergraphs (**Challenge 1**). Moreover, state-of-the-art approaches apply a single RNN to all stocks, thereby ignoring their individual behaviour. The reason being that maintaining a separate model per stock would be intractable with existing techniques. This raises the question of how to model the internal dynamics of stocks efficiently (**Challenge 2**).

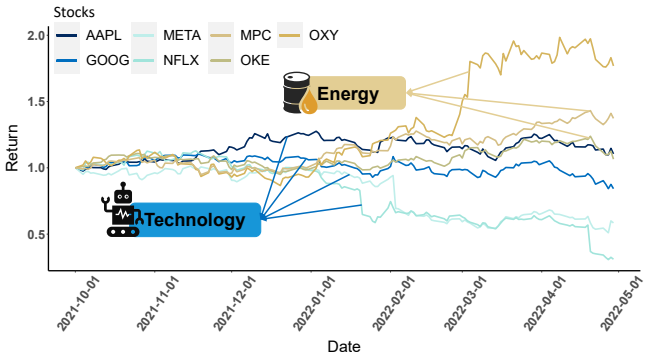


Figure 1: Illustration of complex stock price correlation

In this work, we address the above challenges by proposing **E**fficient **St**ock **I**ntegration with Te**m**poral Generative Filters and Wavelet Hypergraph **Atte**ntions (ESTIMATE), a profit-driven framework for quantitative trading. Based on the aforementioned idea of adopting hypergraphs to capture non-pairwise correlations between stocks, the framework includes two main contributions:

- We present temporal generative filters that implement a hybrid attention-based LSTM architecture to capture the stocks' individual behavioural patterns (**Challenge 2**). These patterns are then fed to hypergraph convolution layers to obtain spatio-temporal embeddings that are optimized with respect to the potential of the stocks for short-term profit.
- We propose a mechanism that combines the temporal patterns of stocks with spatial convolutions through hypergraph attention, thereby integrating the internal dynamics and the multi-order dynamics. Our convolution process uses the wavelet basis, which is efficient and also effective in terms of maintaining the localization (**Challenge 1**).

To evaluate our approach, we report on backtesting experiments for the US market. Here, we try to simulate the real trading actions with a strategy for portfolio management and risk control. The results demonstrate the robustness of our technique compared to existing approaches in terms of stability and return. Our source code and data are available [11].

The remainder of the paper is organised as follows. §2 introduces the problem statement and gives an overview of our approach. We present our new techniques, the temporal generative filters and wavelet hypergraph attentions, in §3 and §4. §5 presents experiments, §6 reviews related works, and §7 concludes the paper.

2 MODEL AND APPROACH

2.1 Problem Formulation

In this section, we formulate the problem of predicting the trend of a stock in the short term. We start with some basic notions.

OHCLV data. At timestep t, the open-high-low-close-volume (OHLCV) record for a stock s is a vector $x_s^t = [o_s^t, h_s^t, l_s^t, c_s^t, v_s^t]$. It denotes the open, high, low, and close price, and the volume of shares that have been traded within that timestep, respectively.

Relative price change. We denote the relative close price change between two timesteps $t_1 < t_2$ of stock s by $d_s^{(t_1,t_2)} = (c_s^{t_2} - c_s^{t_1})/c_s^{t_1}$. The relative price change normalizes the market price variety between different stocks in comparison to the absolute price change.

Following existing work on stock market analysis [9, 41], we focus on the prediction of the change in price rather than the absolute value. The reason being that the timeseries of stock prices are non-stationary, whereas their changes are stationary [19]. Also, this avoids the problem that forecasts often lag behind the actual value [14, 18]. We thus define the addressed problem as follows:

Problem 1 (Stock Movement Prediction). *Given a set S of stocks and a lookback window of k trading days of historic OHLCV records $x_s^{(t-k-1)\ldots t}$ for each stock $s \in S$, the problem of* Stock Movement Prediction *is to predict the relative price change $d_s^{(t,t+w)}$ for each stock in a short-term lookahead window w.*

We formulate the problem as a short-term regression for several reasons. First, we consider a lookahead window over next-day prediction to be robust against random market fluctuations [53]. Second, we opt for short-term prediction, as an estimation of the long-term trend is commonly considered infeasible without the integration of expert knowledge on the intrinsic value of companies and on macroeconomic effects. Third, we focus on a regression problem instead of a classification problem to incorporate the magnitude of a stock's trend, which is important for interpretation [12].

2.2 Design Principles

We argue that any solution to the above problem shall satisfy the following requirements:

- **R1: Multi-dimensional data integration:** Stock market data is multivariate, covering multiple stocks and multiple features per stock. A solution shall integrate these data dimensions and support the construction of additional indicators from basic OHCLV data.

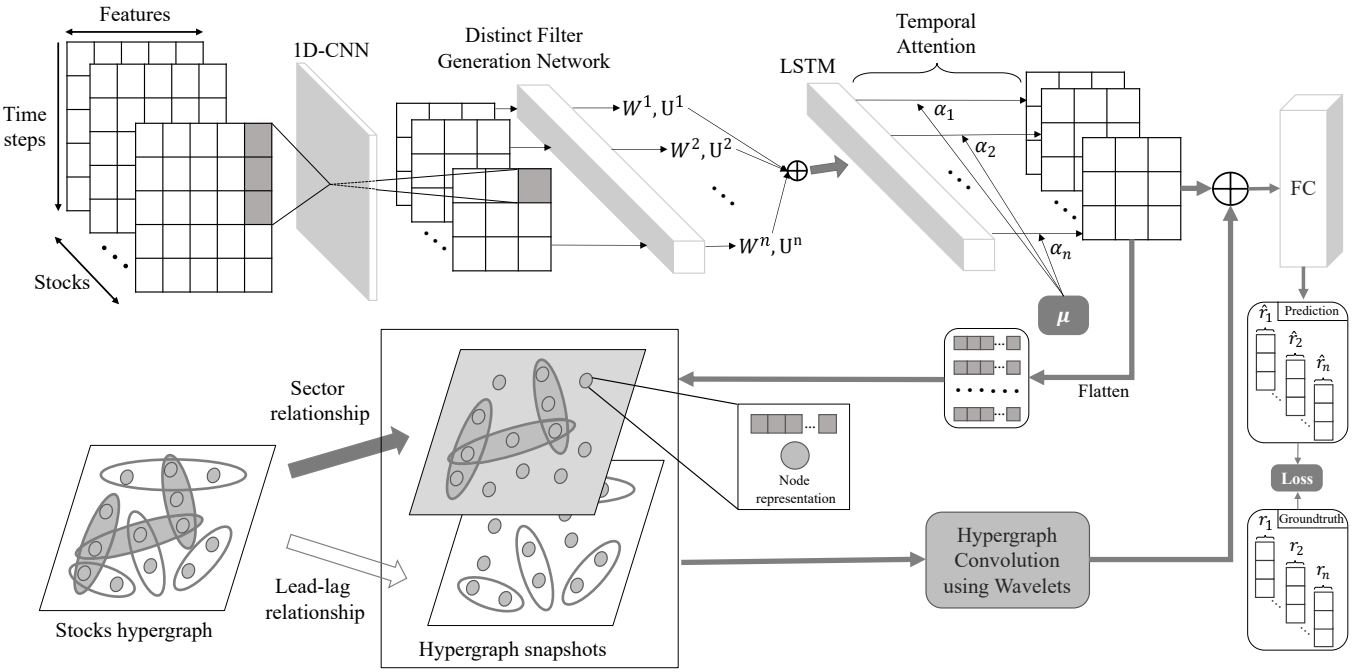


Figure 2: Overview of our framework for stock movement prediction.

- **R2: Non-stationary awareness:** The stock market is driven by various factors, such as socio-economic effects or supply-demand changes. Therefore, a solution shall be robust against non-predictable behaviour of the market.
- **R3: Analysis of multi-order dynamics:** The relations between stocks are complex (e.g., companies may both, cooperate and compete) and may evolve over time. A solution thus needs to analyse the multi-order dynamics in a market.
- **R4: Analysis of internal dynamics:** Each stock also shows some individual behaviour, beyond the multi-order correlations induced by market segments. A solution therefore needs to analyse and integrate such behaviour for each stock.

2.3 Approach Overview

To address the problem of stock movement prediction in the light of the above design principles, we propose the framework shown in Fig. 2. It takes historic data in the form of OHCLV records and derives a model for short-term prediction of price changes per stock.

Our framework incorporates requirement **R1** by first extracting the historic patterns per stock using a temporal attention LSTM. Here, the attention mechanism is used along with a 1D-CNN to assess the impact of the previous timesteps. In addition to the OHCLV data, we employ technical indicators to mitigate the impact of noisy market behaviour, thereby addressing requirement **R2**. Moreover, we go beyond the state of the art by associating the core LSTM parameters with a learnable vector for each stock. It serves as a memory that stores its individual information (requirement **R4**) and results in a system of temporal generative filters. We explain the details of these filters in §3.

To handle multi-order dynamics (requirement **R3**), we model the market with an industry-based hypergraph, which naturally presents non-pairwise relationships. We then develop a wavelet convolution mechanism, which leverages the wavelet basis to achieve a simpler convolution process than existing approaches. We apply a regression loss to steer the model to predict the short-term trend of each stock price. The details of our proposed hypergraph convolution process are given in §4.

3 TEMPORAL GENERATIVE FILTERS

This section describes our temporal generative filters used to capture the internal dynamics of stocks.

Technical indicators. We first compute various technical indicators from the input data in order to enrich the data and capture the historical context of each stock. These indicators, summarized in Table 1, are widely used in finance. For each stock, we concatenate these indicators to form a stock price feature vector x_t on day t. This vector is then forwarded through a multi-layer perceptron (MLP) layer to modulate the input size.

Table 1: Summary of technical indicators used.

Type	Indicators
Trend Indicators	Arithmetic ratio, Close Ratio, Close SMA, Volume SMA, Close EMA, Volume EMA, ADX
Oscillator Indicators	RSI, MACD, Stochastics, MFI
Volatility Indicators	ATR, Bollinger Band, OBV

Local trends. To capture local trends in stock patterns, we employ convolutional neural networks (CNN). By compressing the length of the series of stock features, they help to mitigate the issue of long-term dependencies. As each feature is a one-dimensional timeseries,

we apply one-dimensional filters (1D-CNN) over all timesteps:

$$x_l^k = b_k^l + conv1D(w_{ik}^{l-1}, s_i^{l-1}) \tag{1}$$

where x_l^k represent the input feature at the kth neuron of layer l; b_k^l is the corresponding bias; w_{ik}^{l-1} is the kernel from the ith neuron at layer $l-1$ to the kth neuron at layer l; and s_i^{l-1} is the output of the ith neuron at layer $l-1$.

Temporal LSTM extractor with Distinct Generative Filter. After forwarding the features through the CNNs, we use an LSTM to capture the temporal dependencies, exploiting its ability to memorize long-term information. Given the concatenated feature q_t of the stocks at time t, we feed the feature through the LSTM layer:

$$h_k = LSTM(x_k, h_{k-1}), t - T \leq k \leq t - 1 \tag{2}$$

where $h_k \in \mathbb{R}^d$ is the hidden state for day l and d is the hidden state dimension. The specific computation in each LSTM unit includes:

$$i_t = \sigma(W_{xi}x_t + U_{hi}h_{t-1} + b_i), \qquad f_t = \sigma(W_{xf}x_t + U_{hf}h_{t-1} + b_f),$$
$$g_t = tanh(W_{xg}x_t + U_{hg}h_{t-1} + b_g), \quad o_t = \sigma(W_{xo}x_t + U_{ho}h_{t-1} + b_o),$$
$$c_t = f_t \odot c_{t-1} + i_t \odot g_t, \qquad h_t = o_t \odot tanh(c_t).$$

As mentioned, existing approaches apply the same LSTM to the historical data of different stocks, which results in the learned set of filters ($\mathbb{W} = \{W_{xi}, W_{xf}, W_{xg}, W_{xo}\}, \mathbb{U} = \{U_{xi}, U_{xf}, U_{xg}, U_{xo}\}$) representing the average temporal dynamics. This is insufficient to capture each stock's distinct behaviour (**Challenge 2**).

A straightforward solution would be to learn and store a *set* of LSTM filters, one for each stock. Yet, such an approach quickly becomes intractable, especially when the number of stocks is large.

In our model, we overcome this issue by proposing a memory-based mechanism onto the LSTM network to learn the individual patterns per stock, while not expanding the core LSTM. Specifically, we first assign to each stock i a memory M^i in the form of a learnable m-dimensional vector, $M^i \in \mathbb{R}^m$. Then, for each entity, we feed the memory through a Distinct Generative Filter, denoted by *DGF*, to obtain the weights ($\mathbb{W}^i, \mathbb{U}^i$) of the LSTM network for each stock:

$$\mathbb{W}^i, \mathbb{U}^i = DGF(M^i) \tag{3}$$

Note that *DGF* can be any neural network architecture, such as a CNN or an MLP. In our work, we choose a 2-layer MLP as *DGF*, as it is simple yet effective. As the *DGF* is required to generate a set of eight filters $\{W_{xi}^i, W_{xf}^i, W_{xg}^i, W_{xo}^i, U_{xi}^i, U_{xf}^i, U_{xg}^i, U_{xo}^i\}$ from M^i, we generate a concatenation of the filters and then obtain the results by splitting. Finally, replacing the common filters by the specific ones for each stock in Eq. 2, we have:

$$h_k^i = LSTM(x_k^i, h_{k-1}^i \mid \mathbb{W}^i, \mathbb{U}^i), t - T \leq k \leq t - 1 \tag{4}$$

where h_k^i is the hidden feature of each stock i.

To increase the efficiency of the LSTM, we apply a temporal attention mechanism to guide the learning process towards important historical features. The attention mechanism attempts to aggregate temporal hidden states $\hat{h}_k^i = [h_{t-T}^i, \ldots, h_{t-1}^i]$ from previous days into an overall representation using learned attention weights:

$$\mu(\hat{h}_t^i) = \sum_{k=(t-T)}^{t-1} \alpha_k h_k^i = \sum_{k=(t-T)}^{t-1} \frac{\exp(h_k^{i^T}) W \hat{h}_t^i}{\sum_k \exp(h_k^{i^T}) W \hat{h}_t^i} h_k^i \tag{5}$$

where W is a linear transformation, $\alpha_k = \frac{\exp(h_k^{i^T}) W \hat{h}_t^i}{\sum_k \exp(h_k^{i^T}) W \hat{h}_t^i} h_k^i$ are the attention weights using softmax. To handle the non-stationary nature of the stock market, we leverage the Hawkes process [4], as suggested for financial timeseries in [40], to enhance the temporal attention mechanism in Eq. 5. The Hawkes process is a "self-exciting" temporal point process, where some random event "excites" the process and increases the chance of a subsequent other random event (e.g., a crises or policy change). To realize the Hawke process, the attention mechanism also learns an excitation parameter ϵ_k of the day k and a corresponding decay parameter γ:

$$\hat{\mu}(\hat{h}_t^i) = \sum_{k=(t-T)}^{t-1} \alpha_k h_k^i + \epsilon_k \max(\alpha_k h_k^i, 0) \exp(-\gamma \alpha_k h_k^i) \tag{6}$$

Finally, we concatenate the extracted temporal feature $z_i = \hat{\mu}(\hat{h}_t^i)$ of each stock to form $\mathbf{Z_T} \in \mathbb{R}^{n \times d}$, where n is the number of stocks and d is the embedding dimension.

4 HIGH-ORDER MARKET LEARNING WITH WAVELET HYPERGRAPH ATTENTIONS

To model the groupwise relations between stocks, we aggregate the learned temporal patterns of each stock over a hypergraph that represents multi-order relations of the market.

Industry hypergraph. To model the interdependence between stocks, we first initialize a hypergraph based on the industry of the respective companies. Mathematically, the industry hypergraph is denoted as $\mathbb{G}_i = (S, E_i, w_i)$, where S is the set of stocks and E_i is the set of hyperedges; each hyperedge $e_i \in E_i$ connects the stocks that belong to the same industry. The hyperedge e_i is also assigned a weight w_i that reflects the importance of the industry, which we derive from the market capital of all related stocks.

Price correlation augmentation. Following the Efficient Market Hypothesis [23], fundamentally correlated stocks maintain similar price patterns, which can be used to reveal the missing endogenous relations in addition to the industry assignment. To this end, for the start of each training and testing period, we calculate the price correlation between the stocks using the historical price of the last 1-year period. We employ the lead-lag correlation and the clustering method proposed in [6] to simulate the lag of the stock market, where a leading stock affects the trend of the rests. Then, we form hyperedges from the resulting clusters and add them to E_i. The hyperedge weight is, again, derived from the total market capital of the related stocks. We denote the augmented hypergraph by $\mathbb{G} = (\mathbf{A}, \mathbf{W})$, with $\mathbf{A}$ and $\mathbf{W}$ being the hypergraph incidence matrix and the hyperedge weights, respectively.

Wavelet Hypergraph Convolution. To aggregate the extracted temporal information of the individual stocks, we develop a hypergraph convolution mechanism on the obtained hypergraph $\mathbb{G}$, which consists of multiple convolution layers. At each layer l, the latent representations of the stocks in the previous layer $X^{(l-1)}$ are aggregated by a convolution operator HConv(·) using the topology of $\mathbb{G} = (\mathbf{A}, \mathbf{W})$ to generate the current layer representations X^l:

$$\mathbf{Z^{(l)}} = \mathrm{HConv}(\mathbf{Z^{(l-1)}}, \mathbf{A}, \mathbf{W}, \mathbf{P}) \tag{7}$$

where $\mathbf{X^l} \in \mathbb{R}^{n \times d^l}$ and $\mathbf{X^{l-1}} \in \mathbb{R}^{n \times d^{l-1}}$ with n being the number of stocks and d^{l-1}, d^l as the dimension of the layer-wise latent

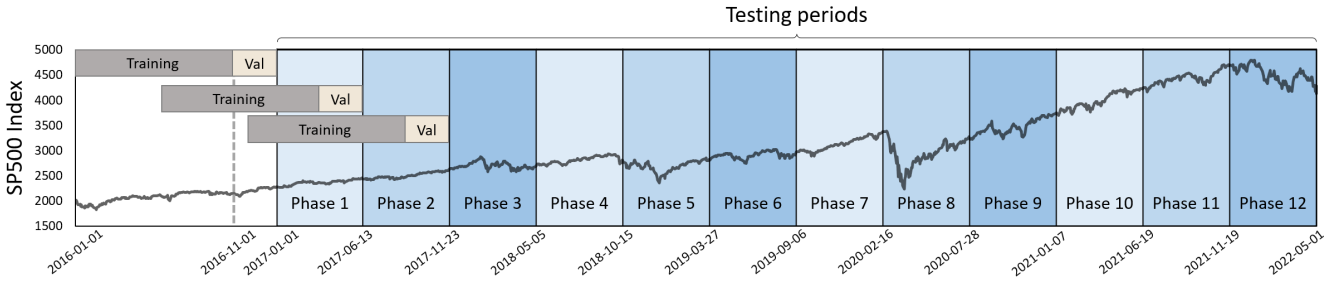


Figure 3: Dataset arrangement for backtesting.

feature; $\mathbf{P}$ is a learnable weight matrix for the layer. Following [51], the convolution process requires the calculation of the hypergraph Laplacian $\mathbf{\Delta}$, which serves as a normalized presentation of $\mathbb{G}$:

$$\mathbf{\Delta} = \mathbf{I} - \mathbf{D_v}^{\frac{1}{2}}\mathbf{A}\mathbf{W}\mathbf{D_e}^{-1}\mathbf{A}^T\mathbf{D_v}^{-1/2} \tag{8}$$

where $\mathbf{D_v}$ and $\mathbf{D_s}$ are the diagonal matrices containing the vertex and hyperedge degrees, respectively. For later usage, we denote $\mathbf{D_v}^{\frac{1}{2}}\mathbf{A}\mathbf{W}\mathbf{D_e}^{-1}\mathbf{A}^T\mathbf{D_v}^{-1/2}$ by $\mathbf{\Theta}$. As $\mathbf{\Delta}$ is a $\mathbb{R}^{n\times n}$ positive semi-definite matrix, it can be diagonalized as: $\mathbf{\Delta} = \mathbf{U}\mathbf{\Lambda}\mathbf{U}^{\mathbf{T}}$, where $\mathbf{\Lambda} = \mathbf{diag}(\lambda_0, \ldots, \lambda_k)$ is the diagonal matrix of non-negative eigenvalues and $\mathbf{U}$ is the set of orthonormal eigenvectors.

Existing work leverages the Fourier basis [51] for this factorization process. However, using the Fourier basis has two disadvantages: (i) the localization during convolution process is not well-maintained [49], and (ii) it requires the direct eigen-decomposition of the Laplacian matrix, which is costly for a complex hypergraph, such as those faced when modelling stock markets (**Challenge 1**). We thus opt to rely on the wavelet basis [49], for two reasons: (i) the wavelet basis represents the information diffusion process [42], which naturally implements localized convolutions of the vertex at each layer, and (ii) the wavelet basis is much sparser than the Fourier basis, which enables more efficient computation.

Applying the wavelet basis, let $\mathbf{\Psi_s} = \mathbf{U_s}\mathbf{\Lambda_s}\mathbf{U_s^T}$ be a set of wavelets with scaling parameter $-s$. Then, we have $\mathbf{\Lambda_s} = \mathbf{diag}(e^{-\lambda_0 s}, \ldots, e^{-\lambda_k s})$ as the heat kernel matrix. The hypergraph convolution process for each vertex t is computed by:

$$HConv(x_t, y) = (\mathbf{\Psi_s}(\mathbf{\Psi_s})^{-1}) \odot (\mathbf{\Psi_s})^{-1}y) = \mathbf{\Psi_s}\mathbf{\Lambda_s}(\mathbf{\Psi_s})^{-1}x_t \tag{9}$$

where y is the filter and $(\mathbf{\Psi_s})^{-1}y$ is its corresponding spectral transformation. Based on the Stone-Weierstrass theorem [49], the graph wavelet $(\mathbf{\Psi_s})$ can be polynomially approximated by:

$$\mathbf{\Psi_s} \approx \sum_{k=0}^{K} \alpha_k(\mathbf{\Delta})^k = \sum_{k=0}^{K} \theta_k(\mathbf{\Theta})^k \tag{10}$$

where K is the polynomial order of the approximation.

The approximation facilitates the calculation of $\mathbf{\Psi_s}$ without the eigen-decomposition of $\mathbf{\Delta}$. Applying it to Eq. 10 and Eq. 7 and choosing LeakyReLU [2] as the activation function, we have:

$$\mathbf{Z_H^{(l)}} = LReLU \sum_{k=0}^{K} ((\mathbf{D_v}^{\frac{1}{2}}\mathbf{A}\mathbf{W}\mathbf{D_e}^{-1}\mathbf{A}^T\mathbf{D_v}^{-1/2})^k \mathbf{Z_H^{(l-1)}}\mathbf{P}) \tag{11}$$

To capture the varying degree of influence each relation between stocks on the temporal price evolution of each stock, we also employ an attention mechanism [40]. This mechanism learns to adaptively weight each hyperedge associated with a stock based on its temporal features. For each node $v_i \in S$ and its associated hyperedge $e_j \in E$, we compute an attention coefficient $\hat{\mathbf{A}}_{ij}$ using the stock's temporal feature x_i and the aggregated hyperedge features x_j, quantifying how important the corresponding relation e_j is to the stock v_i:

$$\hat{\mathbf{A}}_{ij} = \frac{\exp(LReLU(\hat{a}[\mathbf{P}x_i \parallel \mathbf{P}x_j]))}{\sum_{k\in N_i}\exp(LReLU(\hat{a}[\mathbf{P}x_i \parallel \mathbf{P}x_j]))} \tag{12}$$

where $\hat{a}$ is a single-layer feed forward network, $\parallel$ is concatenation operator and $\mathbf{P}$ represents a learned linear transform. N_i is the neighbourhood set of the stock x_i, which is derived from the constructed hypergraph $\mathbb{G}$. The attention-based learned hypergraph incidence matrix $\hat{\mathbf{A}}$ is then used instead of the original $\mathbf{A}$ in Eq. 11 to learn intermediate representations of the stocks. The representation of the hypergraph is denoted by $\mathbf{Z_H}$, which is concatenated with the temporal feature $\mathbf{Z_T}$ to maintain the stock individual characteristic (**Challenge 2**), which then goes through the MLP for dimension reduction to obtain the final prediction:

$$\mathbf{Z} = MLP(\mathbf{Z_T} \parallel \mathbf{Z_H}) \tag{13}$$

Finally, we use the popular root mean squared error (RMSE) to directly encourage the output $\mathbf{X}$ to capture the actual relative price change in the short term $d_s^{(t,t+w)}$ of each stock s, with w being the lookahead window size (with a default value of five).

5 EMPIRICAL EVALUATION

In this section, we empirically evaluate our framework based on four research questions, as follows:

(RQ1) Does our model outperform the baseline methods?
(RQ2) What is the influence of each model component?
(RQ3) Can our model be interpreted in a qualitative sense?
(RQ4) Is our model sensitive to hyperparameters?

Below, we first describe the experimental setting (§5.1). We then present our empirical evaluations, including an end-to-end comparison (§5.2), a qualitative study (§5.4), an ablation test (§5.3), and an examination of the hyperparameter sensitivity (§5.5).

5.1 Setting

Datasets. We evaluate our approach based on the US stock market. We gathered historic price data and the information about industries in the S&P 500 index from the Yahoo Finance database [52], covering 2016/01/01 to 2022/05/01 (1593 trading days). Overall, while the market witnessed an upward trend in this period, it also experienced some considerable correction in 2018, 2020, and 2022. We split the data of this period into 12 phases with varying degrees of

Table 2: Rolling backtesting from 2017-01-01 to 2022-05-01 on the SP500.

	Model	Phase #1	Phase #2	Phase #3	Phase #4	Phase #5	Phase #6	Phase #7	Phase #8	Phase #9	Phase #10	Phase #11	Phase #12	Mean
Return	LSTM	0.064	0.057	0.028	0.058	0.036	-0.032	0.059	-0.139	0.125	0.100	0.062	0.008	0.036
	ALSTM	0.056	0.043	0.022	0.053	0.009	-0.068	0.036	-0.121	0.115	0.097	0.066	0.009	0.026
	HATS	0.102	0.031	-0.003	0.042	0.062	0.067	0.092	-0.074	0.188	0.132	0.063	-0.059	0.054
	LSTM-RGCN	0.089	0.051	0.005	-0.006	0.077	0.019	0.088	-0.121	0.155	0.107	0.038	-0.032	0.039
	RSR	0.065	0.043	-0.009	-0.016	0.014	-0.007	0.059	-0.113	0.089	0.056	0.038	-0.052	0.014
	STHAN-SR	0.108	0.074	0.024	0.016	0.052	0.085	0.090	-0.105	0.158	0.107	0.058	-0.008	0.055
	HIST	0.080	0.020	-0.020	-0.030	-0.050	0.010	-0.030	0.020	0.200	0.100	0.020	-0.050	0.022
	ESTIMATE	**0.109**	**0.080**	**0.025**	**0.105**	**0.051**	**0.135**	**0.149**	**0.124**	**0.173**	**0.065**	**0.147**	**0.057**	**0.102**
IC	LSTM	-0.014	-0.030	-0.016	0.006	0.020	-0.034	-0.006	0.014	-0.002	-0.039	0.022	-0.023	-0.009
	ALSTM	-0.024	-0.025	0.025	-0.009	0.029	-0.018	-0.033	-0.024	0.045	-0.046	0.016	-0.015	-0.007
	HATS	0.013	-0.011	-0.006	-0.005	-0.018	0.029	0.027	-0.002	0.010	-0.017	-0.028	-0.012	-0.002
	LSTM-RGCN	-0.019	0.020	0.024	0.021	-0.005	0.021	0.032	0.035	-0.086	0.043	-0.005	0.030	0.009
	RSR	0.008	-0.009	-0.003	-0.017	-0.009	0.018	0.011	-0.005	-0.036	0.018	-0.058	0.003	-0.007
	STHAN-SR	0.025	-0.015	-0.016	-0.029	0.000	0.018	0.022	0.000	-0.010	0.009	0.007	-0.013	0.000
	HIST	0.003	0.000	0.005	-0.010	0.006	0.008	0.005	-0.017	0.006	0.009	0.011	0.006	0.003
	ESTIMATE	**0.037**	**0.080**	**0.153**	**0.010**	**0.076**	**0.080**	**0.080**	**0.011**	**0.127**	**0.166**	**0.010**	**0.131**	**0.080**
Rank_IC	LSTM	-0.151	-0.356	-0.289	0.089	0.186	-1.091	-0.151	0.201	-0.019	-0.496	0.259	-0.397	-0.185
	ALSTM	-0.211	-0.266	0.409	-0.099	0.182	-0.289	-0.476	-0.243	0.242	-0.323	0.094	-0.174	-0.096
	HATS	0.169	-0.156	-0.139	-0.063	-0.408	0.517	0.333	-0.032	0.085	-0.344	-0.547	-0.135	-0.060
	LSTM-RGCN	-0.271	0.210	0.223	0.152	-0.035	0.279	0.261	0.273	-0.416	0.329	-0.036	0.354	0.110
	RSR	0.151	-0.159	-0.051	-0.213	-0.107	0.282	0.135	-0.090	-0.292	0.175	-0.541	0.040	-0.056
	STHAN-SR	0.690	-0.357	-0.365	-0.714	0.008	0.369	0.523	0.005	-0.265	0.169	0.141	-0.276	-0.006
	HIST	0.085	-0.008	0.125	-0.225	0.192	0.204	0.107	-0.328	0.174	0.256	0.215	0.157	0.080
	ESTIMATE	**0.386**	**0.507**	**1.613**	**0.059**	**0.284**	**0.585**	**0.412**	**0.062**	**0.704**	**0.936**	**0.054**	**0.595**	**0.516**
ICIR	LSTM	-0.010	-0.036	-0.007	0.010	0.016	-0.038	0.004	0.010	0.011	-0.041	0.021	-0.010	-0.006
	ALSTM	-0.057	-0.041	0.030	-0.012	0.033	-0.015	-0.028	-0.034	0.057	-0.053	0.009	-0.002	-0.009
	HATS	0.023	-0.014	0.010	0.001	-0.016	0.033	0.035	0.020	0.023	-0.005	-0.042	-0.034	0.003
	LSTM-RGCN	-0.033	0.012	0.022	0.027	-0.009	0.028	0.047	0.051	-0.085	0.054	-0.006	0.039	0.012
	RSR	0.031	-0.018	-0.005	-0.033	-0.009	0.029	0.001	-0.007	-0 .019	0.017	-0.072	-0.031	-0.010
	STHAN-SR	0.018	-0.011	-0.016	-0.021	0.005	0.016	0.023	0.008	-0.003	0.004	0.009	-0.007	0.002
	HIST	0.004	-0.002	-0.006	-0.001	0.007	0.001	**0.005**	-0.014	0.009	0.009	0.021	0.010	0.004
	ESTIMATE	**0.033**	**0.081**	**0.148**	**0.032**	**0.076**	**0.103**	**0.064**	**0.058**	**0.103**	**0.142**	**0.020**	**0.098**	**0.080**
Rank_ICIR	LSTM	-0.100	-0.364	-0.110	0.140	0.141	-0.984	0.094	0.168	0.117	-0.525	0.227	-0.172	-0.114
	ALSTM	-0.423	-0.344	0.415	-0.134	0.202	-0.192	-0.313	-0.343	0.306	-0.377	0.047	-0.019	-0.098
	HATS	0.234	-0.155	0.179	0.013	-0.221	0.511	0.340	0.270	0.194	-0.076	-0.525	-0.372	0.033
	LSTM-RGCN	-0.387	0.111	0.197	0.170	-0.058	0.313	0.284	0.326	-0.354	0.318	-0.034	0.427	0.109
	RSR	0.378	-0.353	-0.053	-0.285	-0.065	0.326	0.010	-0.081	-0.114	0.131	-0.428	-0.288	-0.068
	STHAN-SR	0.435	-0.211	-0.310	-0.573	0.107	0.386	0.478	0.271	-0.068	0.075	0.230	-0.149	0.056
	HIST	0.079	-0.044	-0.144	-0.020	0.205	0.018	0.122	-0.289	0.236	0.229	0.356	0.209	0.080
	ESTIMATE	**0.315**	**0.446**	**1.344**	**0.178**	**0.307**	**0.587**	**0.329**	**0.311**	**0.541**	**0.885**	**0.100**	**0.488**	**0.486**
Prec@N	LSTM	0.542	0.553	0.581	0.471	0.456	0.569	0.440	0.547	0.588	0.615	0.554	0.608	0.544
	ALSTM	0.583	0.585	0.550	0.471	0.514	0.575	0.431	0.556	0.650	0.518	0.497	0.627	0.546
	HATS	0.624	0.651	0.597	0.495	0.551	0.642	0.532	0.619	0.542	0.550	0.529	0.690	0.585
	LSTM-RGCN	0.565	0.589	0.600	0.505	0.505	0.628	0.522	0.583	0.517	0.538	0.566	0.592	0.559
	RSR	0.587	0.531	0.608	0.455	0.465	0.619	0.473	0.608	0.553	0.618	0.590	0.676	0.565
	STHAN-SR	0.554	0.614	0.573	0.463	0.562	0.611	0.530	0.575	0.553	0.626	0.534	0.510	0.559
	HIST	0.691	0.625	0.476	0.512	0.452	0.561	0.548	0.634	0.463	0.615	0.395	0.605	0.548
	ESTIMATE	**0.619**	**0.631**	**0.673**	**0.524**	**0.540**	**0.739**	**0.568**	**0.669**	**0.611**	**0.679**	**0.547**	**0.724**	**0.627**

volatility, with the period between two consecutive phases being 163 days. Each phase contains 10 month of training data, 2 month of validation data, and 6 month of testing data (see Fig. 3).

Metrics. We adopt the following evaluation metrics: To thoroughly evaluate the performance of the techniques, we employ the following metrics:

- *Return:* is the estimated profit/loss ratio that the portfolio achieves after a specific period, calculated by $NV_e/NV_s - 1$, with NV_s and NV_e being the net asset value of the portfolio before and after the period.
- *Information Coefficient (IC):* is a coefficient that shows how close the prediction is to the actual result, computed by the average Pearson correlation coefficient.
- *Information ratio based IC (ICIR):* The information ratio of the IC metric, calculated by $ICIR = mean(IC)/std(IC)$
- *Rank Information Coefficient (Rank_IC):* is the coefficient based on the ranking of the stocks' short-term profit potential, computed by the average Spearman coefficient [24].
- *Rank_ICIR:* Information ratio based Rank_IC (ICIR): The information ratio of the Rank_IC metric, calculated by: $rank_ICIR = mean(rank_IC)/std(rank_IC)$
- *Prec@N:* evaluates the precision of the top N short-term profit predictions from the model. This way, we assess the capability of the techniques to support investment decisions.

Baselines. We compared the performance of our technique with that of several state-of-the-art baselines, as follows:

- *LSTM:* [13] is a traditional baseline which leverages a vanilla LSTM on temporal price data.
- *ALSTM:* [9] is a stock movement prediction framework that integrates the adversarial training and stochasticity simulation in an LSTM to better learn the market dynamics.

- *HATS:* [18] is a stock prediction framework that models the market as a classic heterogeneous graph and propose a hierarchical graph attention network to learn a stock representation to classify next-day movements.
- *LSTM-RGCN:* [19] is a graph-based prediction framework that constructs the connection among stocks with their price correlation matrix and learns the spatio-temporal relations using a GCN-based encoder-decoder architecture.
- *RSR:* [10] is a stock prediction framework that combines Temporal Graph Convolution with LSTM to learn the stocks' relations in a time-sensitive manner.
- *HIST:* [50] is a graph-based stock trend forecasting framework that follows the encoder-decoder paradigm in attempt to capture the shared information between stocks from both predefined concepts as well as revealing hidden concepts.
- *STHAN-SR:* [40] is a deep learning-based framework that also models the complex relation of the stock market as a hypergraph and employs vanilla hypergraph convolution to learn directly the stock short-term profit ranking.

Trading simulation. We simulate a trading portfolio using the output prediction of the techniques. At each timestep, the portfolio allocates an equal portion of money for k stocks, as determined by the prediction. We simulate the risk control by applying a trailing stop level of 7% and profit taking level of 20% for all positions. We ran the simulation 1000 times per phase and report average results.

Reproducibility environment. All experiments were conducted on an AMD Ryzen ThreadRipper 3.8 GHz system with 128 GB of main memory and four RTX 3080 graphic cards. We used Pytorch for the implementation and Adam as gradient optimizer.

5.2 End-to-end comparisons

To answer research question RQ1, we report in Table 2 an end-to-end comparison of our approach (ESTIMATE) against the baseline methods. We also visualize the average accumulated return of the baselines and the S&P 500 index during all 12 phases in Fig. 4.

In general, our model outperforms all baseline methods across all datasets in terms of *Return*, *IC*, *Rank_IC* and *Prec@10*. Our technique consistently achieves a positive return and an average *Prec@10* of 0.627 over all 12 phases; and performs significant better than the S&P 500 index with higher overall return. STHAN-SR is the best method among the baselines, yielding a high *Return* in some phases (#1, #2, #5, #10). This is because STHAN-SR, similar to our approach, models the multi-order relations between the stocks using a hypergraph. However, our technique still outperforms STHAN-SR by a considerable margin for the other periods, including the ranking metric *Rank_IC* even though our technique does not aim to learn directly the stock rank, like STHAN-SR.

Among the other baseline, models with a relational basis like RSR, HATS, and LSTM-RGCN outperform vanilla LSTM and ALSTM models. However, the gap between classic graph-based techniques like HATS and LSTM-RGCN is small. This indicates that the complex relations in a stock market shall be modelled. An interesting finding is that all the performance of the techniques drops significantly during phase #3 and phase #4, even though the market moves sideways. This observation highlights issues of prediction algorithm when there is no clear trend for the market.

The training times for these techniques are shown in Fig. 5, where we consider the size of training set ranging from 40 to 200 days. As expected, the graph-based techniques (HATS, LSTM-RGCN, RSR, STHAN-R, HIST and ESTIMATE) are slower than the rest, due to the trade-off between accuracy and computation time. Among the graph-based techniques, there is no significant difference between the techniques using classic graphs (HATS, LSTM-RGCN) and those using hypergraphs (ESTIMATE, STHAN-R). Our technique ESTIMATE is faster than STHAN-R by a considerable margin and is one of the fastest among the graph-based baselines, which highlights the efficiency of our wavelet convolution scheme compared to the traditional Fourier basis.

5.3 Ablation Study

To answer question RQ2, we evaluated the importance of individual components of our model by creating four variants: *(EST-1)* This variant does not employ the hypergraph convolution, but directly uses the extracted temporal features to predict the short-term trend of stock prices. *(EST-2)* This variant does not employ the generative filters, but relies on a common attention LSTM by existing approaches. *(EST-3)* This variant does not apply the price-correlation based augmentation, as described in §4. It employs solely the industry-based hypergraph as input. *(EST-4)* This variant does not employ the wavelet basis for hypergraph convolution, as introduced in §4. Rather, the traditional Fourier basis is applied.

Table 3: Ablation test

Metric	ESTIMATE	EST-1	EST-2	EST-3	EST-4
Return	**0.102**	0.024	0.043	0.047	0.052
IC	**0.080**	0.013	0.020	0.033	0.020
RankIC	**0.516**	0.121	0.152	0.339	0.199
Prec@N	**0.627**	0.526	0.583	0.603	0.556

Table 3 presents the results for several evaluation metrics, averaged over all phases due to space constraints. We observe that our full model *ESTIMATE* outperforms the other variants, which provides evidence for the the positive impact of each of its components. In particular, it is unsurprising that the removal of the relations between stocks leads to a significant degradation of the final result (approximately 75% of the average return) in *EST-1*. A similar drop of the average return can be seen for *EST-2* and *EST-3*, which highlights the benefits of using generati +ve filters over a traditional single LSTM temporal extractor (*EST-2*); and of the proper construction of the representative hypergraph (*EST-3*). Also, the full model outperforms the variant *EST-4* by a large margin in every metric. This underlines the robustness of the convolution with the wavelet basis used in *ESTIMATE* over the traditional Fourier basis that is used in existing work.

5.4 Qualitative Study

We answer research question RQ3 by visualizing in Fig. 6 the prediction results of our technique ESTIMATE for the technology stocks APPL and META from 01/10/2021 to 01/05/2022. We also compare ESTIMATE's performance to the variant that does not consider relations between stocks (EST-1) and the variant that does not employ temporal generative filters (EST-2). This way, we illustrate how our technique is able to handle **Challenge 1** and **Challenge 2**.

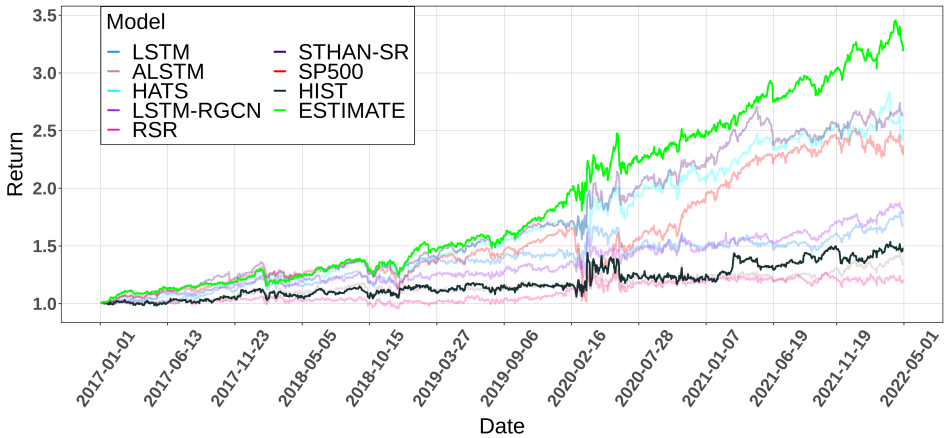


Figure 4: Cumulative return.

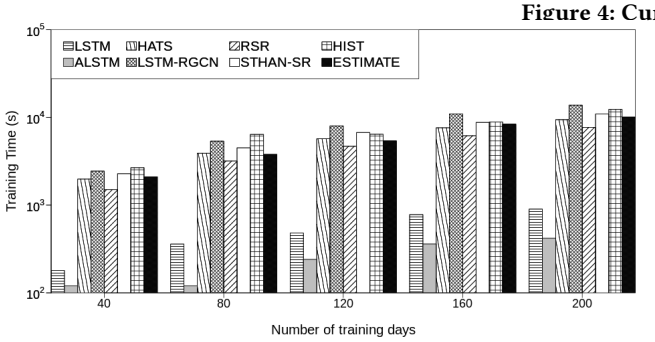


Figure 5: Training performance.

The results indicate that modelling the complex multi-order dynamics of a stock market (**Challenge 1**) helps ESTIMATE and EST-2 to correctly predict the downward trend of technology stocks around the start of 2022; while the prediction of EST-1, which uses the temporal patterns of each stock, suffers from a significant delay. Also, the awareness of internal dynamics of ESTIMATE due to the usage of generative filters helps our technique to differentiate the trend observed for APPL from the one of META, especially at the start of the correction period in January 2022.

5.5 Hyperparameter sensitivity

This experiment addresses question RQ4 on the hyperparameter sensitivity. Due to space limitations, we focus on the most important hyperparameters. The backtesting period of this experiment is set from 01/07/2021 to 01/05/2022 for the same reason.

Lookback window length T. We analyze the prediction performance of ESTIMATE when varying the length T of the lookback window in Fig. 7. It can be observed that the best window length is 20, which coincides with an important length commonly used by professional analyses strategies [1]. The performance drops quickly when the window length is less or equal than 10, due to the lack of information. On the other hand, the performance also degrades when the window length increases above 25. This shows that even when using an LSTM to mitigate the vanishing gradient issue, the model cannot handle very long sequences.

Lookahead window length w. We consider different lengths w of the lookahead window (Fig. 7) and observe that ESTIMATE achieves the best performance for a window of length 5. The results degrade significantly when w exceeds 10. This shows that our model performs well for short-term prediction, it faces issues when considering a long-term view.

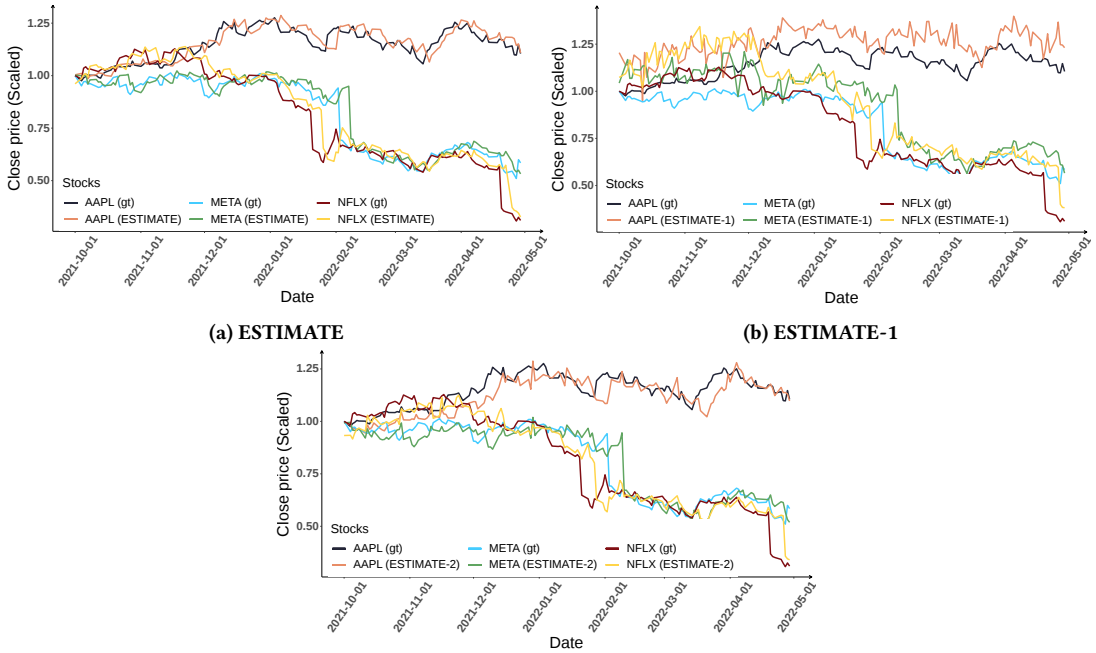
Number of selected top-k stocks. We analyze the variance in the profitability depending on the number of selected top-k stocks from the ranking in Fig. 7. We find that ESTIMATE performs generally well, while the best results are obtained for k = 10.

6 RELATED WORK

Traditional Stock Modelling. Traditional techniques often focus on numerical features [21, 39], referred to as technical indicators, such as the Moving Average (MA) or the Relative Strength Index (RSI). The features are combined with classical timeseries models, such as ARIMA [37], to model the stock movement [3]. However, such techniques often require the careful engineering by experts to identify effective indicator combinations and thresholds. Yet, these configurations are often not robust against market changes.

For individual traders, they often engineer rules based on a specific set of technical indicators (which indicate the trading momentum) to find the buying signals. For instance, a popular strategy is to buy when the moving average of length 5 (MA5) cross above the moving average of length 20 (MA20), and the Moving Average Convergence Divergence (MACD) is positive. However, the engineering of the specific features requires the extensive expertise and experiment of the traders in the market. Also, the traders must continuously tune and backtest the strategy, as the optimized strategy is not only different from the markets but also keeps changing to the evolving of the market. Last but not least, it is exhaustive for the trader to keep track of a large number of indicators of a stock, as well as the movement of multiple stocks in real time. Due to these drawbacks, quantitative trading with the aid of the AI emerges in recent years, especially with the advances of deep neural network (DNN).

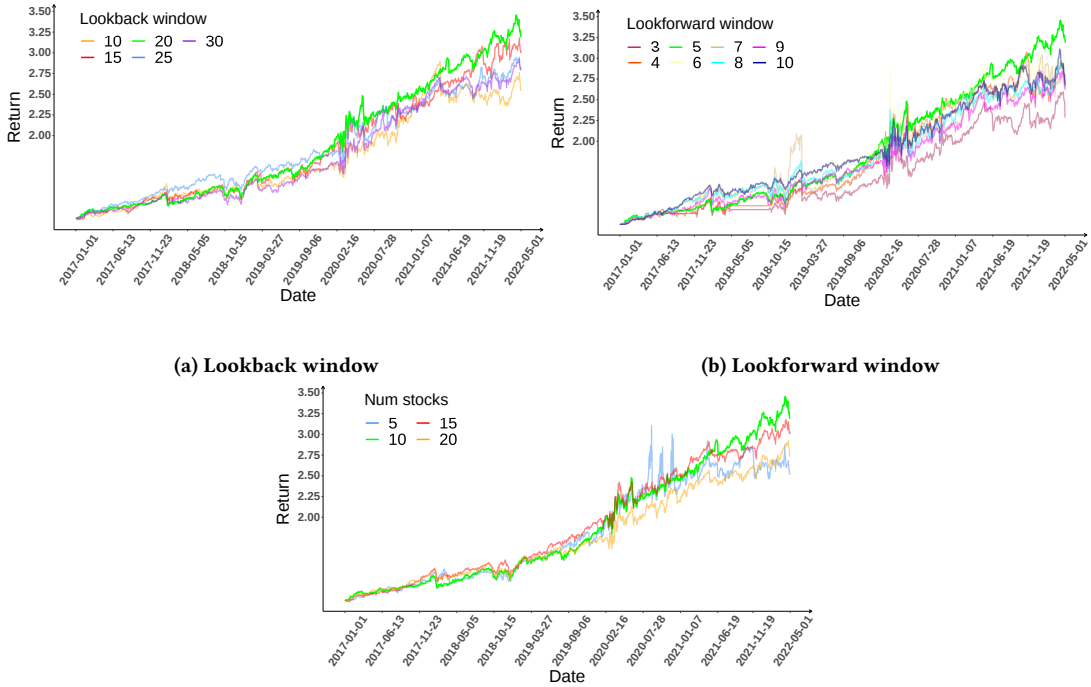
DNN-based Stock Modelling. Recent techniques leverage advances in deep learning to capture the non-linear temporal dynamics of stock prices through high-level latent features [5, 17, 38]. Earlier techniques following this paradigm employ recurrent neural networks (RNN) [25] or convolutional neural networks (CNN) [47] to model a single stock price and predict its short-term trend. Other works employ deep reinforcement learning (DRL), the combination



(a) ESTIMATE **(b) ESTIMATE-1**

(c) ESTIMATE-2

Figure 6: Trend prediction



(a) Lookback window **(b) Lookforward window**

(c) Num stocks

Figure 7: Hyperparameters sensitivity

of deep learning with reinforcement learning (RL), a subfield of sequential decision-making. For instance, the quantitative trading problem can be formulated as a Markov decision process [22] and be addressed by well-known DRL algorithms (e.g. DQN, DDPG [20]). However, these techniques treat the stocks independently and lack a proper scheme to consider the complex relations between stocks in the market.

Graph-based Stock Modelling. Some state-of-the-art techniques address the problem of correlations between stocks and propose graph-based solutions to capture the inter-stock relations. For instance, the market may be modelled as a heterogeneous graph with different type of pairwise relations [18], which is then used in an attention-based graph convolution network (GCN) [8, 29, 32, 33, 43, 46] to predict the stock price and market index movement. Similarly, a market graph may be constructed and an augmented GCN with temporal convolutions can be employed to learn, at the same time, the stock movement and stock relation evolution [19]. The most recent techniques [10, 40] are based on the argument that the stock market includes multi-order relations, so that the market should be modelled using hypergraphs. Specifically, external knowledge from knowledge graphs enables the construction of a market hypergraph [40], which is used in a spatiotemporal attention hypergraph network to learn interdependences of stocks and their evolution. Then, a ranking of stocks based on short-term profit is derived.

Different from previous work, we propose a market analysis framework that learns the complex multi-order correlation of stocks derived from a hypergraph representation. We go beyond the state of the art ([10, 40]) by proposing temporal generative filters that implement a memory-based mechanism to recognize better the individual characteristics of each stock, while not over-parameterizing the core LSTM model. Also, we propose a new hypergraph attention convolution scheme that leverages the wavelet basis to mitigate the high complexity and dispersed localization faced in previous hypergraph-based approaches.

7 CONCLUSION

In this paper, we address two unique characteristics of the stock market prediction problem: (i) *multi-order dynamics* which implies strong non-pairwise correlations between the price movement of different stocks, and (ii) *internal dynamics* where each stock maintains its own dedicated behaviour. We propose *ESTIMATE*, a stock recommendation framework that supports learning of the multi-order correlation of the stocks (i) and their individual temporal patterns (ii), which are then encoded in node embeddings derived from hypergraph representations. The framework provides two novel mechanisms: First, *temporal generative filters* are incorporated as a memory-based shared parameter LSTM network that facilitates learning of temporal patterns per stock. Second, we presented attention hypergraph convolutional layers using the wavelet basis, i.e., a convolution paradigm that relies on the polynomial wavelet basis to simplify the message passing and focus on the localized convolution.

Extensive experiments on real-world data illustrate the effectiveness of our techniques and highlight its applicability in trading recommendation. Yet, the experiments also illustrate the impact of concept drift, when the market characteristics change from the training to the testing period. In future work, we plan to tackle this issue by exploring time-evolving hypergraphs with the ability to memorize distinct periods of past data and by incorporating external data sources such as earning calls, fundamental indicators, news data [28, 34, 35], social networks [30, 31, 44, 45], and crowd signals [15, 16, 27].

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A TECHNICAL INDICATORS FORMULATION

In this section, we express equations to formulate indicators described in **Section 3: Temporal Generative Filters.** Let t denote the t-th time step and O_t, H_t, L_t, C_t, V_t represents the open price, high price, low price, close price, and trading volume at t-th time step, respectively. Since most of the indicators are calculated within a certain period, we denote n as that time window.

- Arithmetic ratio (AR): The open, high, and low price ratio over the close price.
$$AR_O = \frac{O_t}{C_t}, AR_H = \frac{H_t}{C_t}, AR_L = \frac{L_t}{C_t} \tag{14}$$
- Close Price Ratio: The ratio of close price over the highest and the lowest close price within a time window.
$$\begin{aligned} RC_{min_t} &= \frac{C_t}{\min([C_t, C_{t-1}, ..., C_{t-n}])} \\ RC_{max_t} &= \frac{C_t}{\max([C_t, C_{t-1}, ..., C_{t-n}])} \end{aligned} \tag{15}$$
- Close SMA: The simple moving average of the close price over a time window
$$SMA_{C_t} = \frac{C_t + C_{t-1} + ... + C_{t-n}}{n} \tag{16}$$
- Close EMA: The exponential moving average of the close price over a time window
$$EMA_{C_t} = C_t * k + EMA_{C_{t-1}} * (1 - k) \tag{17}$$
where: $k = \frac{2}{n+1}$
- Volume SMA: The simple moving average of the volume over a time window
$$SMA_{V_t} = \frac{V_t + V_{t-1} + ... + V_{t-n}}{n} \tag{18}$$
- Volume EMA: The exponential moving average of the close price over a time window
$$EMA_{V_t} = V_t * k + EMA_{V_{t-1}} * (1 - k) \tag{19}$$
where: $k = \frac{2}{n+1}$
- Average Directional Index (ADX): ADX is used to quantify trend strength. ADX calculations are based on a moving average of price range expansion over a given period of time.
$$\begin{aligned} DI_t^+ &= \frac{\text{Smoothed } DM^+}{ATR_t} * 100 \\ DI_t^- &= \frac{\text{Smoothed } DM^-}{ATR_t} * 100 \\ DX_t &= \frac{DI_t^+ - DI_t^-}{DI_t^+ + DI_t^-} * 100 \\ ADX_t &= \frac{ADX_{t-1} * (n-1) + DX_t}{n} \end{aligned} \tag{20}$$
where:
  - $DM^+ = H_t - H_{t-1}$
  - $DM^- = L_{t-1} - L_t$
  - Smoothed $DM^{+/-} = DM_{t-1} - \frac{DM_{t-1}}{n} + DM_t$
  - ATR: Average True Range
- Relative Strength Index (RSI): measures the magnitude of recent price changes to evaluate overbought or oversold conditions in the price of a stock or other asset. It is the normalized ration of the average gain over the average loss.

$$
\begin{aligned}
avgGain_t &= \frac{(n-1) * avgGain_{t-1} + gain_t}{n} \\
avgLoss_t &= \frac{(n-1) * avgLoss_{t-1} + loss_t}{n} \\
RSI_t &= 100 - \frac{100}{1 + \frac{avgGain_t}{avgLoss_t}}
\end{aligned} \tag{21}
$$

where:
- $gain_t = \begin{cases} C_t - C_{t-1}, & \text{if } C_t > C_{t-1} \\ 0, & \text{otherwise} \end{cases}$
- $loss_t = \begin{cases} 0, & \text{if } C_t > C_{t-1} \\ C_{t-1} - C_t, & \text{otherwise} \end{cases}$

- Moving average convergence divergence (MACD): shows the relationship between two moving averages of a stock's price. It is calculated by the subtraction of the long-term EMA from the short-term EMA.

$$MACD_t = EMA_t(n = 12) - EMA_t(n = 26) \tag{22}$$

where:
- $EMA_t(n = 12)$: The exponential moving average at t-th time step of the close price over 12-time steps.
- $EMA_t(n = 26)$: The exponential moving average at t-th time step of the close price over 26-time steps.

- Stochastics: an oscillator indicator that points to buying or selling opportunities based on momentum

$$Stochastic_t = 100 * \frac{Cur_t - L_{t-n}}{H_{t-n} - L_{t-n}} \tag{23}$$

where:
- $TP_t = \frac{H_t + L_t + C_t}{3}$
- $moneyFlow_t = TP_t * Volume_t$
- $posMF_t = posMF_{t-1} + moneyFlow_t$ if $TP_t > TP_{t-1}$
- $negMF_t = negMF_{t-1} + moneyFlow_t$ if $TP_t \leq TP_{t-1}$

- Money Flow Index (MFI): an oscillator measures the flow of money into and out over a specified period of time. The MFI is the normalized ratio of accumulating positive money flow (upticks) over negative money flow values (downticks).

$$MFI_t = 100 - \frac{100}{1 + \frac{\sum_{t-n}^{t} posMF}{\sum_{t-n}^{t} negMF}} \tag{24}$$

where:
- $TP_t = \frac{H_t + L_t + C_t}{3}$
- $moneyFlow_t = TP_t * Volume_t$
- $posMF_t = posMF_{t-1} + moneyFlow_t$ if $TP_t > TP_{t-1}$
- $negMF_t = negMF_{t-1} + moneyFlow_t$ if $TP_t \leq TP_{t-1}$

- Average of True Ranges (ATR): The simple moving average of a series of true range indicators. True range indicators show the max range between *(High - Low), (High-Previous_Close), and (Previous_Close - Low).*

$$
\begin{aligned}
TR_t &= \text{Max}(H_t - L_t, |H_t - C_{t-1}|, |L_t - C_{t-1}|) \\
ATR_t &= \frac{1}{n} \sum_{i=t-n}^{t} TR_i
\end{aligned} \tag{25}
$$

- Bollinger Band (BB): a set of trendlines plotted two standard deviations (positively and negatively) away from a simple moving average (SMA) of a stock's price.

$$
\begin{aligned}
BOLU_t &= MA_t(TP_t, w) + m * \sigma[TP_t, w] \\
BOLD_t &= MA_t(TP_t, w) - m * \sigma[TP_t, w]
\end{aligned} \tag{26}
$$

where:
- $BOLU_t$: Upper Bollinger Band at t-th time step
- $BOLD_t$: Lower Bollinger Band at t-th time step
- MA_t: Moving average at t-th time step
- $TP_t = \frac{H_t + L_t + C_t}{3}$
- m: number of standard deviations (typically 2)
- $\sigma[TP, n]$: Standard deviation over last w periods of TP

- On-Balance Volume (OBV): measures buying and selling pressure as a cumulative indicator that adds volume on up days and subtracts volume on down days.

$$OBV_t = OBV_{t-1} + \begin{cases} V_t, & \text{if } C_t > C_{t-1} \\ 0, & \text{if } C_t = C_{t-1} \\ -V_t, & \text{if } C_t < C_{t-1} \end{cases} \tag{27}$$