Trade When Opportunity Comes: Price Movement Forecasting via Locality-Aware Attention and Adaptive Refined Labeling

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Abstract—Price movement forecasting aims at predicting the future trends of financial assets based on the current market conditions and other relevant information. Recently, machine learning (ML) methods have become increasingly popular and achieved promising results for price movement forecasting in both academia and industry. Most existing ML solutions formulate the forecasting problem as a classification (to predict the direction) or a regression (to predict the return) problem in the entire set of training data. However, due to the extremely low signal-to-noise ratio and stochastic nature of financial data, good trading opportunities are extremely scarce. As a result, without careful selection of potentially profitable samples, such ML methods are prone to capture the patterns of noises instead of real signals. To address the above issues, we propose a novel framework—LARA (Locality-Aware Attention and Adaptive Refined Labeling), which contains the following three components: 1) Locality-aware attention automatically extracts the potentially profitable samples by attending to their label information in order to construct a more accurate classifier on these selected samples. 2) Adaptive refined labeling further iteratively refines the labels, alleviating the noise of samples. 3) Equipped with metric learning techniques, Locality-aware attention enjoys task-specific distance metrics and distributes attention on potentially profitable samples in a more effective way. To validate our method, we conduct comprehensive experiments on three real-world financial markets: ETFs, the China’s A-share stock market, and the cryptocurrency market. LARA significantly outperforms existing baseline models. Moreover, LARA achieves superior performance compared with the traditional time-series analysis methods and a set of machine learning based competitors on the Qlib platform. Extensive ablation studies and experiments demonstrate that LARA indeed captures more reliable trading opportunities. Our project homepage is available.

Index Terms—Price movement forecasting, Locality-aware attention, Adaptive refined labeling

I. INTRODUCTION

Price movement forecasting is one of the most important and challenging problems in quantitative finance. It is notoriously difficult partly because the financial market is highly stochastic, dynamic, and volatile \(^1\). The classical Efficient Market Hypothesis (EMH) (e.g., \(^2\), \(^3\)) states that in an informationally efficient market, price changes must be forecastable if all relevant information is reflected immediately. However, in the real-world financial markets, perfect efficiency is impossible to achieve in practice \(^4\) due to informational asymmetry and “noisy” behaviors among the traders \(^5\). Indeed, hundreds of abnormal returns have been discovered in the literature (see the classical review by Grossman and Stiglitz \(^6\) and the recent lists \(^7\), \(^8\)). As the more recent endeavor to “beat the market” and achieve excess returns, machine learning based solutions, taking advantage of the nonlinear expressive power, have become increasingly popular and achieved promising results (e.g., \(^1\), \(^9\)–\(^13\)).

The most straightforward way to employ machine learning techniques to financial forecasting problems consists of the following two steps \(^9\). First, mining effective factors (either manually or automatically, e.g., \(^14\)) correlated/predictive with asset returns, including fundamental factors, technical factors, economic factors, and alternative factors. Second, feeding these factors as features into some off-the-shelf machine learning algorithms to generate trading signals. Recently, much effort has been devoted to designing new machine learning algorithms in the second step to make more precise predictions (e.g., \(^10\), \(^12\), \(^15\), \(^16\)). Most work mentioned above trains the model over the entire set of training data (typically spans a consecutive period of time)\(^\text{\(\star\)}\). However, it is well known that financial time-series data has an extremely low signal-to-noise ratio \(^1\), to the degree that modern machine algorithms are prone to pick up patterns of noises instead of real profitable signals (a.k.a. overfit the training set). Without careful selection of potentially profitable samples from the entire set of training data, tuning the models to generalize well can be very challenging \(^10\), \(^17\). Even for most trading experts, asset prices behave like (almost) unpredictable random walks most of the time, and good trading opportunities only happen occasionally. In the light of this fact, we argue that

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\(^\text{\(\star\)}\)Note that in financial time-series forecasting problems, one should not split the training and testing set randomly, since the data points are not i.i.d., but strongly and temporally correlated.
it can be more effective and robust to concentrate on specific samples that are potentially more predictable and profitable, as the proverb says, *trade when opportunity comes*.

We explain our motivation with an intuitive analog of evaluating students’ academic performance shown in Fig. 1. According to the history of students’ performance, we regard the excellent students as positive samples and the ordinary students as negative samples. Excellent students typically get higher scores than ordinary ones in a single exam. Besides, excellent students are more likely to have the better and similar performance. It inspires us to first extract the potentially profitable samples (excellent students) according to their local similar performance and then construct a more accurate classifier on these selected samples (e.g., Fig. 1(a)-(b)). However, financial samples are only labeled once. If only one exam is observed, it is too hard for us to make a comprehensive evaluation so that we may miss some excellent students and choose the ordinary ones by mistake. We take more extra exams to evaluate each student comprehensively, just like constructing multiple predictors to predict one financial sample. The ordinary students mixed into the group of excellent students can be easily distinguished via multiple exams (analogy to red noisy samples located in Fig. 1(b)). It inspires us to further denoise the labels of noisy samples with multiple predictors.

Motivated by this observation, there arise two critical challenges: how to extract potentially profitable samples (challenge 1) and how to denoise the labels of noisy samples adaptively (challenge 2). To tackle challenge 1, we propose the *locality-aware attention* method to explicitly extract potentially profitable samples (Sec. III-A). To tackle challenge 2, we propose a new denoising method called *adaptive refined labeling* (Sec. III-B). Putting two parts together, we propose our novel and effective framework named LARA (Locality-Aware Attention and Adaptive Refined Labeling). See Fig. 2 for an overview of LARA.

For challenge 1, we propose the *locality-aware attention* method, which has two main components: a *metric learning module* for constructing a better metric, and a *localization module* for explicitly extracting potentially profitable samples. Specifically, the Euclidean distance is a widely used distance metric but it does not fit the high-dimensional financial datasets, as it neglects the inherent relations among different features [13]. It motivates us to introduce the first component—the *metric learning module*, which can learn a more compatible distance metric [19], [20] assisting the *localization module*. The second component—*localization module*—intends to model an auxiliary relation between the inputs and the labels of historical data to extract a better subset of potentially profitable samples. To fulfill the idea, one alternative solution is to utilize the classical Nadaraya–Watson kernel regression method [21] to weigh the labels according to the inputs’ locations. Furthermore, we propose the *masked attention* scheme by integrating label information in the local neighborhood to obtain potentially profitable samples.

For challenge 2, we observe that in the actual financial market, two samples may have similar features but yield completely opposite labels because of stochastic and chaotic nature of financial datasets [22]. Such noisy samples, i.e., similar samples with opposite labels, interfere with the prediction of the model [23]. Thus, we propose a novel method, called *adaptive refined labeling*, to adaptively reset labels of these noisy samples to the opposite ones to boost the performance of predictors (shown in Fig. 2(d)). Through the empirical results, refining the labels of financial samples in an iterative manner can reduce the influence of noisy samples. Additionally, we observe a steady improvement when iterating the *adaptive refined labeling* method several times and combining all the iterated predictors.

The main contributions can be summarized as follows:

- (Section III-A) We propose the hierarchical *locality-aware attention* method to first extract potentially profitable samples by attending to the label information and then construct a more accurate classifier on these selected samples. Moreover, we use a *metric learning module* to learn a well-suited distance metric assisting the *localization module*.

- (Section III-B) We propose the *adaptive refined labeling* method to reset the labels of noisy samples iteratively. Furthermore, we combine the iterated models to boost the performance of the predictors.

- (Section V) We conduct comprehensive experiments on three real-world financial markets. Experimental results show that our model significantly outperforms the traditional time-series analysis methods and a set of machine learning competitors on the Qib platform [16]. Besides, extensive ablation studies and experiments demonstrate the effectiveness of each component of LARA and suggest that LARA can indeed capture the more reliable trading opportunities.

II. Preliminary

**Problem Definition.** We study the binary classification task of the asset price trend. At the t-th time step, let \((x_t, y_t)\) denote a data point, where \(x_t \in \mathcal{X} \subseteq \mathbb{R}^d\) is the feature vector with its corresponding label \(y_t \in \mathcal{Y} = \{0, 1\}\). We intend to build a binary parameterized classifier \(f_\theta : \mathcal{X} \rightarrow \mathcal{Y}\), and \(f_\theta(x) = Pr(y = 1)\) represents the probability of the positive prediction. We denote the training data as \(X = [x_1, \cdots, x_N]^T \in \mathbb{R}^{N \times d}\), where the vector \(x_t\) represents the sample at time \(t\). Similarly, let the testing data be \(X_{test} = [x_{1}, \cdots, x_{N_{test}}]^T \in \mathbb{R}^{N_{test} \times d}\).
Labeling Methods. For long and short positions, we build individual models respectively. We use a fixed-time horizon method to label samples \[\mathbb{I}\]. Concretely, the label \(y_t\) indicates whether the return of the corresponding sample over a time horizon \(\Delta\) exceeds a certain threshold \(\lambda\). For long positions:

\[
y_t = \begin{cases} 
1 & \frac{p_{t+\Delta}}{p_t} - 1 > \lambda \\
0 & \text{otherwise}
\end{cases},
\]

where \(\lambda\) is a pre-defined threshold, and we vary it for specific tasks. \(p_t\) and \(p_{t+\Delta}\) denote the price at time \(t\) and \((t+\Delta)\). Similarly, for short positions, we set the label 1 as \(\frac{p_t}{p_{t+\Delta}} - 1 < -\lambda\) and 0 otherwise.

Precision. In quantitative trading, we care more about samples with the positive prediction, because these samples can lead us to identify real trading opportunities. Hence, precision is an important criterion to evaluate different models, which can be calculated as

\[
\text{Precision} = \frac{TP}{TP + FP},
\]

where: \(TP = \text{True Positive}\); \(FP = \text{False Positive}\).

Samples with high \(p_x\). Assume that we only take one sample of the label \(y\) in an independent Bernoulli distribution \(y_i|\{x\} \sim \text{Ber}(p_x)\) conditioned on known information \(x\), where \(p_x\) is the probability of success in a trial. A larger \(p_x\) indicates a stronger tendency and lower uncertainty and the prediction at this moment is more reliable. Hence we gather the samples with high \(p_x\), whose \(p_x\) is greater than a given threshold \((\text{thres})\), i.e., \(p_x > \text{thres}\). However, it is impossible to obtain the exact underlying probability \(p_x\) from the dataset as we can only observe one instance of \(y_i|\{x\} \sim \text{Ber}(p_x)\). Thus, we propose locality-aware attention (Sec. III-A) to give an approximate estimation \(\hat{p}_x\).

III. LOCALITY-AWARE ATTENTION AND ADAPTIVE REFINED LABELING

In this section, we propose our LARA framework, which is composed of the following two main components in order—locality-aware attention (Sec. III-A) and adaptive refined labeling (Sec. III-B), shown in Fig. 2. The key idea is that locality-aware attention can extract the samples with high \(p_x\) and adaptive refined labeling can reset the labels of noisy samples to boost the performance of predictors.

A. Locality-Aware Attention

1) Localization Module:
Recalling that \(y_{i|\{x\}} \sim \text{Ber}(p_x)\), it is hard to recover Bernoulli’s distribution \(\text{Ber}(p_x)\) from the dataset, as we can only observe one single instance of label \(y_{i|\{x\}}\). Suppose the probability parameter \(p_x\) that determines each distribution is continuous with respect to \(x\). We design a localization module attending to other observed labels in the dataset to obtain an approximate estimation \(\hat{p}_x\) of \(p_x\). In the light of the concepts of attention mechanism [24], let \((x_i, y_i)\) denote the key-value pair and \(x\) be the query sample processed by the metric learning module (introduced in Sec. III-A2). The localization module can be formulated as follows:

\[
\hat{p}_x = \frac{\sum_{1 \leq i \leq N} y_i \frac{k(x_i, x)}{\sum_{1 \leq j \leq N} k(x_j, x)}}{N},
\]

where \(N\) is the size of the training set, \(k(x_i, x)\) is the attention weight (importance) between \(x\) and \(x_i\), and the label of \(x_i\) is \(y_i\). However, in the most general attention mechanisms, the model allows every sample to attend to every other sample. Intuitively, closer neighbors of a query point have greater similarity than neighbors which are further away. We inject the locality structure into the scheme by performing masked attention and merely pay attention to the neighbors of \(x\), i.e., \(\{z : z \in \mathcal{N}(x)\}\). Then we reformulate the localization module as follows:

\[
\hat{p}_x = \frac{\sum_{z \in \mathcal{N}(x)} y_z \frac{k(z, x)}{\sum_{z \in \mathcal{N}(x)} k(z, x)}}{|\mathcal{N}(x)|}.
\]

Furthermore, there exist several reasonable metrics for the implementation of the attention weight in [4]. We recommend two natural approaches: the first is the identical weight and the second is the reciprocal of Euclidean distance \(d(z, x)\) considering the influence of distance, detailed as below:

\[
k(z, x) = \begin{cases} 
k_i & k_r = 1/d(z, x), \text{the identical weight} \\
k_r & \text{the reciprocal of distance}
\end{cases}
\]

In addition, to obtain the neighbors in the localization module, we propose two practical paradigms (detailed in Sec. III-C): first, to search the k-nearest neighbors of the query point (K-Neighbor); second, to search the k-nearest neighbors in a given fixed radius (R-Neighbor).
Specifically, in the training phase, we first extract the samples with high \( p_x \) satisfying \( \hat{p}_x > \text{thres} \) in locality-aware attention (LA-Attention), which implicitly represent the potentially profitable samples. Then we train the more robust model on these selected samples according to the corresponding supervised loss. In the testing phase, we first gather the potentially profitable samples. Then we train the more robust model with adaptive refined labeling for selected samples. In the testing phase, we first gather the samples with high \( p_x \) by the \( \hat{p}_x > \text{thres} \) criterion, and then we only make predictions on these selected samples. Through empirical observations, LA-Attention can largely improve the precision of the prediction model, which constitutes the two-stage training and testing schemes, shown in Algorithm 3.

2) Metric Learning Module:
Many approaches in machine learning require a measure of the distance among data points. Traditionally, practitioners would choose a standard distance metric (Euclidean, City-Block, Cosine, etc.) using prior domain knowledge. Indeed, different investors have different understanding of the financial market and prefer completely different types of factors, e.g., value investors prefer fundamental factors, while active investors focus on technical factors. In order to enhance the flexibility of LARA, we turn to the metric learning technique to mitigate the pressure of manually searching for the suitable distance measurement of different factors. LARA automatically learns a proper distance metric in a given feature space. We adopt the Sparse High-Dimensional Metric Learning (SDML) algorithm, an efficient sparse metric learning technique in high-dimensional space via double regularization, introduced in [25], and equip it in LARA as shown in Fig. 2. Overall, we use the metric learning module to learn a well-suited distance metric assisting the localization module to extract potentially profitable samples.

B. Adaptive Refined Labeling

Price movement is notoriously difficult to forecast because financial markets are complex dynamic systems [22]. Indeed, we observe that some training samples get the high (low) probability of the positive prediction \( \hat{Pr}(y = 1) \), but their labels might also be negative (positive). Thus, we name them as the noisy samples. We propose to reset the labels of these noisy samples to the opposite ones, i.e., positive training samples with the extremely low predicted probability are modified to the negative label, and vice versa. Then we retrain another predictor based on the refined dataset with the modified labels. In addition, our method runs in an iterative fashion. In each iteration of the training phase, it refines the labels of noisy samples adaptively. In particular, denote the refined labels in the \( i \)-th iteration as \( Y_i \). We sort training samples according to the probability of the positive prediction in descending order. The process of refining positive samples to the negative can be described as resetting the last \( (N \times r) \) labels in \( Y_{i+1} \) to 0, where \( r \) is the exchange ratio taking the value from \([0, 1]\). Meanwhile, the process of refining negative samples to the positive can be described as resetting the first \( (N \times r) \) labels in \( Y_{i+1} \) to 1. At last, we combine all the iterated predictors using the following proposed approaches:

- **Last:** making a prediction from the last iterated predictor.
- **Vote:** making a prediction that averages all iterated predictors.

An illustration using the vote combining method is shown in Fig. 3. We can find that, in iteration 1, the weak learners can discriminate the vast majority of samples correctly, except for only one misclassified sample. In iteration 2, the algorithm further classifies all samples correctly after resetting two noisy samples’ labels adaptively and combining two more predictors. This modification can be incorporated into existing machine learning codes easily: Add the \((4 – 6)\)-th line in Algorithm 1 to refine the labels of the top and bottom \((N \times r)\) samples. Finally, we combine all the trained models so far to boost the performance of predictors.

C. Implementation

As the localization module needs to estimate attention weights to extract potentially profitable samples, a straightforward approach is to calculate the distance between all possible pairs of samples, which is computationally expensive when considering the quadratic explosion with respect to the number
of datasets. We utilize our proposed masked attention scheme to calculate attention weights located in the neighborhood of each sample, i.e., $\mathcal{N}(x)$. However, it is still time-consuming to accurately search for the neighbors $\mathcal{N}(x)$ of the corresponding sample $x$. Then we adopt a fast approximate nearest neighbor search method called HNSW [26], and it provides more than 100 times speedup to approximately query the nearest neighbors. In particular, we propose two schemes to obtain the neighbors of each sample based on the HNSW algorithm: the first is to search for the K-nearest neighbors (K-Neighbor) and the second is to search for the nearest neighbors in a fixed radius (R-Neighbor). The HNSW algorithm can be directly adopted in K-Neighbor. As for R-Neighbor, we first query the nearest neighbors with the moderate value of $K$ and then select potentially profitable samples located in a fixed radius. As introduced in Sec. III-A we consider two kinds of attention weights: the identical weight $k_i$ to implement the K-Neighbor algorithm and the reciprocal of distance $k_r$ to implement the R-Neighbor algorithm. The pseudocode for the K-Neighbor/R-Neighbor algorithm and the reciprocal of distance $k$ weights: the identical weight $k$.

Algorithm 2: K-Neighbor and R-Neighbor Algorithm

**Input:** Training data $(X, Y) \in \mathbb{R}^{N \times d} \times \mathbb{R}^N$, the query sample $x$, the number of the nearest neighbors $K$, and the radius $R$.

**Output:** $\hat{p}_x \in \mathbb{R}^N$.

**K-Neighbor Algorithm:**
1. $\mathcal{N}(x) = \text{top } K \text{ points with minimum } d(z, x), z \in X$.
2. Return: $\hat{p}_x = \sum_{z \in \mathcal{N}(x)} y_z \frac{k_i(z, x)}{\sum_{z \in \mathcal{N}(x)} k_i(z, x)}$.

**R-Neighbor Algorithm:**
1. $\mathcal{N}_1(x) = \text{top } K \text{ points with minimum } d(z, x), z \in X$.
2. $\mathcal{N}_2(x) = \{z : z \in \mathcal{N}_1(x), d(x, z) < R\}$.
3. Return: $\hat{p}_x = \sum_{z \in \mathcal{N}_2(x)} y_z \frac{k_r(z, x)}{\sum_{z \in \mathcal{N}_2(x)} k_r(z, x)}$.

Algorithm 3 describes the whole process of the LARA framework. As we study the binary classification problem, we use the binary cross-entropy loss in RA-Labeling. Note that the localization module in LARA does not rely on specific methods as the backbone predictor. For the sake of simplicity, we use LightGBM [27], a commonly used GBDT open-sourced implementation, as the base predictor in our experiments. The RA-Labeling method can also be used in conjunction with other machine learning algorithms to denoise the noisy samples in quantitative trading. Thus, LARA is a versatile framework, and existing deep learning methods of price movement forecasting can be also integrated into the framework.

Algorithm 3: LARA framework

**Input:** Training data $(X, Y) \in \mathbb{R}^{N \times d} \times \mathbb{R}^N$, testing data $X_{test} \in \mathbb{R}^{N_{test} \times d}$, the initial model $f_{\theta_0}$, threshold $\text{thres}$, hyper-parameters $k, r$.

**Output:** $Y_{out} \in \mathbb{R}^N$.

1. ▷ Training phase:
2. Init empty set $X', Y'$.
3. for $(x, y)$ in $(X, Y)$ do
4. Estimate $\hat{p}_x$ via Eq. (4) with the query sample $x$ and the key-value pair $(x_i, y_i) \in (X, Y)$.
5. if $\hat{p}_x > \text{thres}$ then $X' \leftarrow \{x \}; Y' \leftarrow \{y\}$.
6. $f_{\theta_{[k]}} = \text{RA-Labeling (} X', Y', f_{\theta_0}, k, r \text{)}$.
7. ▷ Testing phase:
8. Init empty set $X'_{test}$.
9. for $x_{test}$ in $X_{test}$ do
10. Estimate $\hat{p}_{x_{test}}$ via Eq. (4) with the query sample $x_{test}$ and the key-value pair $(x_i, y_i) \in (X, Y)$.
11. if $\hat{p}_{x_{test}} > \text{thres}$ then $X'_{test} \leftarrow \{x_{test}\}$.
12. Return: $Y_{out} = f_{\theta_{[k]}}(X'_{test})$.

IV. MORE DISCUSSIONS

In this section, we use two examples to illustrate why the LA-Attention can help extract potentially profitable samples and be robust to noise. Finally, we discuss the computational complexity of LARA.

A. Locality-Aware Attention

We use a visual and intuitive example to further understand the effectiveness of the metric learning module incorporated into the locality-aware attention method, as shown in Fig. 3. We plot the feature embedding of the randomly sampled 1000 points in the ETF market dataset using t-SNE [28]. In order to obtain the more real trading signals, we intend to search for as many samples with high $p_x$ by the $\hat{p}_x$ via $\text{thres}$ criterion as possible ($\text{thres}$ equals 0.5 in this demo). In Fig. 3(a), the positive and negative points in the original dataset are mixed together and there are 174 positive samples in total, which have the return distribution with almost the zero mean and are hard to discriminate effectively. After introducing the localization module (Fig. 3(b)), more positive samples (279) are found and the return distribution of potentially profitable samples is obviously larger than zero, which indicates the effectiveness of LA-Attention. However, the negative ones still dominate all samples. Further combined with the metric learning module, in Fig. 3(c), we can see the number of the positive samples (424) accounts for about one-half of all samples and the learned embedding has a more compact structure and clearer distinct boundaries. The return distribution is larger than the zero mean with a greater margin. Hence, this learned distance metric can assist the locality-aware attention method to further boost the estimation of samples with high $p_x$.

B. Masked Attention Scheme

We run the masked attention scheme on a simple example for further study in Fig. 5. We can obtain samples with high $p_x$ in the blue region calculated by the masked attention scheme, whose labels are indeed dominated by the positive ones. We use an SVM classifier with the Gaussian kernel to distinguish positive and negative samples and get the blue
decision boundary located in the mixing region of positive and negative samples. However, when we train the classifier only on the samples with high $p_x$, we can get the red decision boundary located in the blue region, which can be more robust to the noise of datasets and generate real profitable signals.

C. Discussion of Computational Complexity

Recall that there are $N$ samples in the training phase and $N_{\text{test}}$ samples in the testing phase. Each sample has $d$-dimensional features. Metric learning (SDML) intends to build a $d \times d$ sparse Mahalanobis distance matrix. Thanks to the low dimension in our task (only 40), the optimization speed is very fast. For LA-Attention, the main time consumption is to search for the neighbors of each sample. Hence, it takes $O((2N + N_{\text{test}}) \log(N))$ in the LA-Attention method in total when considering $O(N \log(N))$ for the construction of data structure and takes $O(\log(n))$ to search for the neighbors of each sample. Moreover, RA-Labeling repeats the training and testing process $K$ times, so it takes about $O(K (N_1 T_c + T_p))$ in the training and testing phase. Note that searching for neighbors in the LA-Attention method, constructing the tree estimators, and predicting the results can all be well paralleled, so we can react quickly in the actual financial market.

V. EXPERIMENTS

To demonstrate the effectiveness of our proposed LARA framework, we further conduct extensive experiments on three real-world financial markets: ETFs (an exchange traded fund market), the China’s A-share market (a securities exchange), and OKEx (a cryptocurrency exchange).

Our algorithm has been fielded in HuTai Security, one of the largest security brokerages in China. ETFs are traded in huge volumes in Chinese exchanges and the markets are also extremely competitive. We compare our framework LARA on four liquid Chinese ETFs with a set of baseline models: time-series analysis methods, standard machine learning algorithms, and several ablated variants of LARA (Sec. V-B). We also execute a simple back-testing trading strategy to qualify LARA’s performance comprehensively.

To further evaluate LARA in different trading markets with much longer periods and various granularities, we conduct additional extensive experiments with the China’s A-share market and OKEx dataset (Sec. V-C) on the Qlib platform [16], which is a popular open-sourced quantitative investment platform based on the latest AI technologies. Compared with a series of deep learning algorithms in the Quant Model Zoo in Qlib, we show that LARA captures the more reliable trading opportunities and achieves superior performance against a set of competitors.

A. Experimental Environment

We conduct all experiments with the following settings:

- Operating system: Ubuntu 5.4.0-6ubuntu1 16.04.12;
- CPU: Intel(R) Xeon(R) Gold 6230 CPU @ 2.10GHz;
- GPU: NVIDIA GP102GL [Tesla P40];
- Software versions: Python 3.7; Numpy 1.19.2; Pandas 1.0.5; Lightgbm 2.2.3; scikit-learn 0.23.2; hnswlbi 0.4.0; Scipy 1.5.2; Metric-learn 0.6.2; pyqlib 0.6.2.

B. LARA to Trade ETFs

A series of experiments on ETFs show the following results:
(1) LA-Attention significantly improves the performance when applied in both the training and the testing phase (Sec. V-B2).
(2) LARA framework outperforms other 8 traditional time-series analysis and a set of machine learning algorithms (Sec. V-B3).
(3) LARA is insensitive to the tuning of hyper-parameters (Sec. V-B4).

1) Experimental Settings:

Dataset Collection. We conduct experiments over four high-frequency Chinese exchange-traded funds (ETF) datasets: 159915.SZ, 512480.SH, 512880.SH, and 515050.SH. All of them are liquid and traded in large volumes in the exchange.
In our experiments, we chronologically split the data into three time periods for training (from Jan. 1, 2020 to Apr. 17, 2020), validation (Apr. 20, 2020 to May. 29, 2020), and testing (from Jun. 1 2020 to Jul. 6 2020). The granularity of the high-frequency ETFs dataset is tick-level (3-second), the forecasting horizon (Δ) is 1 minute, the forecasting threshold (λ) is 1E-3, and we summarize the basic statistics in Table I. As can be seen, there are about 440,000 trading instances on average for each ETF dataset and the proportion of positive and negative instances is roughly between 10%–20%. Note that the time range covers several important economic crisis events, such as the 2020 financial market crash and COVID-19. Finally, we utilize ten-level price-volume central limit order books (CLOBs) datasets to construct the input features. Each record contains the last price, amount, volume, IOPV, and ten-level price-volume data, which are fundamental elements of ETFs transactions. In our experiment, we collect 40 features based on commonly used alpha factors [29], [30], which are broadly divided into two types. The first one comprises technical factors and limit-order book factors, such as moving average of price [31] and buy/sell pressure indicators [31]. The second one consists of some specific ETF factors, such as the weighted return among the constituent stocks of the corresponding ETF [32]. For the complete factor list, please refer to the project webpage.

As depicted in Table I, due to space limit, we only show the experimental results of 512480.SH, one of the mostly used benchmark ETFs, to play a representative role. The results for other ETFs can be found in the webpage.

Performance Metrics. In this paper, we use the following commonly used financial metrics to evaluate the performance of LARA comprehensively [33]–[35].

- **Win-Loss Ratio (WLR)** is the ratio of the average mean of winnings to the average mean of losses for the entire trading period. It measures the profitability for each of the winnings in excess of that for each of the losses:

\[ WLR = \frac{E[\text{Return of winning}]}{E[\text{Return of loss}]} . \]  

- **Average Return (AR)** is a basic and direct index to evaluate the performance of the corresponding strategy in the high-frequency trading environment. It represents the average return per transaction or the expected profit of each trade:

\[ AR = \frac{\text{Sum of Returns}}{\#\text{Transactions}} . \]  

- **Transactions** is an important indicator for high-frequency trading to compare different methods with the same frequency of trades. It is defined as follows:

\[ \#\text{Transactions} = \text{The number of trades} . \]  

Parameter Settings. We use Sparse High-Dimensional Metric Learning (SDML) [25] in the metric learning module. We adopt a fast approximate nearest neighbor search method called HNSW [26] to implement the K-Neighbor/R-Neighbor algorithm in LA-Attention (detailed in Sec. III-C) efficiently. We employ the LightGBM [27] as the machine learning predictor in the LARA framework since it has been reported to be the most common predictor for financial datasets in several previous works [11], [15]. The combining methods we use in RA-Labeling are **vote** and **last**, which are described in Sec. III-B. For LARA, we obtain the best hyper-parameters on the validation set using the grid search method, and the search space is listed as follows:

- \( K \) in K-Neighbor \( \in \{10, 20, 30, \cdots, 150\} \);
- \( R \) in R-Neighbor \( \in \{10, 20, 30, \cdots, 100\} \);
- \( k \) in RA-Labeling method \( \in \{1, 3, 5, 7, 9\} \);
- \( r \) in RA-Labeling method \( \in \{0.01, 0.02, \cdots, 0.10\} \).

In all experiments, we keep using their default hyper-parameter settings of the metric learning module, LA-Attention, and RA-

### TABLE I

**Details of the Datasets.**

| Dataset   | #Instances | Granularity | Δ       | λ       | Positive(Ratio) | Negative(Ratio) |
|-----------|------------|-------------|---------|---------|-----------------|-----------------|
| ETF       | 159915.SZ  | 448,360     | 3 secs  | 1 min   | 1E-3            | 60,141 (13.41%) | 58,344 (13.01%) |
|           | 512480.SH  | 433,231     | 3 secs  | 1 min   | 1E-3            | 99,907 (23.06%) | 102,967 (23.77%) |
|           | 512880.SH  | 448,613     | 3 secs  | 1 min   | 1E-3            | 97,579 (21.75%) | 99,775 (22.24%) |
|           | 515050.SH  | 459,648     | 3 secs  | 1 min   | 1E-3            | 53,457 (11.63%) | 52,399 (11.40%) |
| Stock     | A-share Market | 859,230    | 1 day   | 1 day   | 1E-3            | 409,487 (47.66%) | - |
| Cryptocurrency | BTC/USDT | 10,865,879 | 0.1 sec | 10 secs | 1E-4 | 4,265,413 (39.26%) | - |

### TABLE II

**Ablation experimental results with masked attention scheme applied in the training and the testing phase. Best results are in bold. - means we do not use the LA-Attention in the corresponding phase.**

| Applied Phases | Training Phase | Testing Phase | Precision(%) | Win-Loss Ratio | Average Return | #Transactions |
|----------------|----------------|---------------|--------------|----------------|----------------|---------------|
|                |                |               |             |                |                |               |
| -              | -              | -             | 70.16±0.89  | 2.872±0.106    | 0.00166±0.0002 | 1000          |
| -              | LA-Attention   | -             | 70.39±1.07  | 2.757±0.184    | 0.00166±0.0002 | 1000          |
| LA-Attention   | -              | -             | 37.82±11.09 | 1.712±0.188    | 0.00062±0.00037 | 1000          |
| LA-Attention   | LA-Attention   |               | 78.58±0.67  | 2.957±0.259    | 0.00196±0.0003 | 1000          |

\[ \]
aggregates individual predictions to form a final prediction. Regressors on random subsets of original datasets and then use the squared-loss using the stochastic gradient descent. This model optimizes the loss function to update the parameters. This model optimizes the final prediction.

Combines through a weighted majority vote to produce the final prediction. Repeatedly modified sample weight of the data and then by learning simple decision rules inferred from features. Models that "explains" a given time series based on its own lags and the lagged forecast errors. A class of models that can be divided into three main classes: 

- **Trading Signals.** In high-frequency quantitative trading, the number of trades is an important criterion to measure the opening frequency of trading strategies. According to [32], it is a rational way to obtain the top confident samples to compare predictive ability fairly among different methods. Thus, we retrieve the top 100, 200, 500, and 1000 samples with the highest classification probability to generate trading signals.

- **Trading Strategies.** The asset positions are not limited. At the time \( t \), if the model gives a positive signal, we open a new long position and close this position 1 minute later. Similarly, we open new short positions for the negative signals and close these positions 1 minute later.

**Compared Methods.** We compare with the following methods in our experiments: it can be divided into three main classes:

1. **Time-Series Analysis Methods** [10]:
   - Ordinary Least Squares (OLS) fits a linear model to minimize the residual square sum among observed targets.
   - Autoregressive Integrated Moving Average (ARIMA) is a class of models that “explains” a given time series based on its own lags and the lagged forecast errors.

2. **Machine Learning Methods** [9]:
   - Ridge regression minimizes a penalized residual sum of squares by imposing a penalty on the size of the coefficients.
   - Decision Trees create a model that predicts target values by learning simple decision rules inferred from features.
   - AdaBoost [36] fits a sequence of weak learners on repeatedly modified sample weight of the data and then combines through a weighted majority vote to produce the final prediction.
   - Bagging Regressor is an ensemble estimator that fits base regressors on random subsets of original datasets and then aggregates individual predictions to form a final prediction.
   - Multi-Layer Perceptron (MLP) trains iteratively \( w.r.t \) the loss function to update the parameters. This model optimizes the squared-loss using the stochastic gradient descent.

   - **LightGBM** [27] is an efficient implementation of gradient boosting decision tree (GBDT). This method also serves as the base classifier in our LARA framework.

   (3) **LARA:** To validate the contribution of the two main components of LA-Attention (Sec. III-A) and RA-Labeling (Sec. III-B), we ablate them separately and test the following experiments: i) LA-Attention: ii) RA-Labeling: iii) LA-Attention + RA-Labeling.

2. **Ablation Experimental Results:**

The main contribution of our proposed LA-Attention is that it extracts the potentially profitable samples (with high \( p_x \)) by attending to the local financial label information and constructs the more accurate classifier on these selected samples. So we should explore whether concentrating on the samples with high \( p_x \) using LA-Attention can boost the performance of predictors? For the sake of fair comparison, we retrieve the 1000 samples with the top positive probability in the testing dataset and probe into the RA-Labeling method. We compare different performance metrics of retrieved samples considering whether to use the LA-Attention method in the training and testing phase.

In Table II, the LA-Attention method applied in both the training and testing phase outperforms other ablation competitors on the Precision, Win-Loss Ratio, and Average Return index, which is in line with our expectations that LA-Attention can produce much more profitable signals with a significantly higher average return. If we merely use LA-Attention in the testing phase, the performance decreases slightly by about 8% on the precision index. This suggests that the noisy samples may interfere with the learned predictor [23]. However, merely using LA-Attention in the training phase can lead to significant performance degradation (about 40% on the precision index) unexpectedly. We postulate the reason is that the distributions of datasets in the training and testing phase deviate greatly from each other. This ablation experiment tells that we should pay attention to the samples with high \( p_x \) in both the training and testing phases to get more reliable trading opportunities and achieve significant improvement over profit.

3. **Comparison Experimental Results:**

First, we quantitatively evaluate our proposed methods compared with traditional time-series analysis and machine learning algorithms to demonstrate the effectiveness of our approaches. For a fair comparison, we generate trading signals according to the top 1000 probability values. As shown in
Table III presents the results of 512480.SH. LARA achieves the highest performance of all three indicators under the same #Transactions: Precision, Win-Loss Ratio, and Average Return. We improve the performance with a great margin by up to 8% over precision compared with other time-series and machine learning algorithms. With RA-Labeling, the precision improves by 1-2% and the variance among different seeds decreases significantly, which suggests RA-Labeling can empirically reduce noise of financial datasets. In order to investigate the effect of the number of trades, in Fig. 6, we choose three representative methods with the highest precision index, i.e., OLS in traditional time-series analysis, LightGBM in machine learning, and our proposed LARA framework to compare the precision and average return metric on 512480.SH. We can find that LARA consistently outperforms the OLS and LightGBM method regarding precision and average return considering the different numbers of trades.

| Methods                          | Precision(%) | Win-Loss Ratio | Average Return | #Transactions |
|----------------------------------|--------------|----------------|----------------|---------------|
| Time Series                      |              |                |                |               |
| Ordinary Least Squares           | 52.22±0.21   | 2.430±0.017    | 0.00127±0.00000| 1000          |
| ARIMA                            | 12.57±2.77   | 0.919±0.073    | -0.00006±0.00012| 1000          |
| Machine Learning                 |              |                |                |               |
| AdaBoost                         | 51.32±3.23   | 1.935±0.055    | 0.00115±0.00008| 1000          |
| Bagging Regressor                | 62.14±1.56   | 2.187±0.183    | 0.00161±0.00004| 1000          |
| MLP                              | 43.53±17.89  | 1.838±0.293    | 0.00093±0.00048| 1000          |
| Ridge                            | 53.58±0.22   | 2.754±0.009    | 0.00129±0.00001| 1000          |
| Decision Trees                   | 34.48±1.44   | 1.487±0.111    | 0.00067±0.00005| 1000          |
| LightGBM                         | 70.16±0.89   | 2.872±0.106    | 0.00166±0.00002| 1000          |
| LARA + LA-Attention              | 78.36±1.14   | 2.934±0.241    | 0.00196±0.00004| 1000          |
| LARA + RA-Labeling               | 71.03±0.60   | 2.913±0.097    | 0.00168±0.00001| 1000          |
| LARA + LA-Attention + RA-Labeling| 79.53±0.67   | 2.933±0.221    | 0.00198±0.00002| 1000          |

Fig. 7. Quantitative comparisons over cumulative return between baseline and LARA on 512480.SH.

Second, we illustrate the performance of the back-testing strategy regarding the cumulative return shown in Fig. 7. We choose the top 1000 signals with the highest predicted probability value for a fair comparison and do not limit the number of positions. The right y-axis illustrates the volatility on each trading day. Transaction costs are ignored since our transaction number is the same. If you are really concerned about transaction costs, just minus some constant on all methods, and it does not affect the conclusion according to experimental results. In Fig. 7, it is obvious that LARA always outperforms other methods along the test period, which demonstrates the effectiveness of our proposed method to enhance the prediction of the asset price trend.

Third, we plot the open and cut positions in Fig. 8 to illustratively explain how our proposed methods work. LARA achieves favorable profit in both long and short positions. Even though the forecasting target is 0.1%, more than half of the transactions have earned 0.2% return, and some even reach 0.4%, which shows that LARA has indeed captured satisfactory and profitable trading opportunities. Besides, we can find that on up-trend period, we open long positions (red triangles in Fig. 8); in the down-trend period, we open short positions (blue triangles in Fig. 8). Obviously, it is a rational way to open positions when there is a stronger tendency in the price of ETF and omit them when it just fluctuates.

4) Parameter Study:
In this section, we investigate the sensitivity of parameters on our proposed methods.

Analysis of LA-Attention. For two implementations of LA-Attention, K-Neighbor and R-Neighbor (Sec. III-A), we explore the effect of points $K$ in the K-Neighbor algorithm and points $K$ and radius $R$ in the R-Neighbor algorithm. We can find in Fig. 9(a), as the number of points in the K-Neighbor algorithm increases, the precision index of most ETFs gradually increases, except 512880.SH. The same situation occurs in Fig. 9(b). The more points we attend to, the better performance we can get. However, it costs more time when attending to more neighbors, which is a trade-off between time and performance. Besides, the radius $R$ in the R-Neighbor algorithm is stable for the experimental results given a fixed $K$ shown in Fig. 9(b). These results demonstrate the LA-Attention method is stable for the tuning of hyper-parameters.

Analysis of RA-Labeling. We conduct experiments to analyze the robustness of two combining methods in RA-Labeling (Sec. III-B) with the different iteration number $k$ and
Fig. 8. Overview of open and cut positions on 512480.SH.

Fig. 9. Parameter study. (a)(b) Effect of $K$ and $R$ in K-Neighbor and R-Neighbor. (c)(d) Effect of $k$ and $r$ in RA-Labeling. Results shown in (b,c,d) are obtained on 512480.SH.

exchange ratio $r$. In Fig. 9(c), labeling-last performs better as $r$ increases, and the precision is further improved in labeling-vote, which suggests the effectiveness of RA-Labeling. A similar phenomenon appearing in Fig. 9(d), as $k$ increases, Labeling-vote has achieved increasingly better performance on the precision index and reached the saturated performance when $r$ is larger than 7.

C. LARA to Trade Stocks and Cryptocurrencies in Qlib

To further qualify LARA in different trading markets with longer periods and various granularities, we transplant our proposed LARA framework to a recently launched Qlib platform [16] to evaluate its performance on the China’s A-share market and OKEx with a set of deep learning based competitors. Extensive experiments demonstrate the effectiveness of LARA against a set of competitors.

1) Experimental Settings:
For stocks, following Quant Dataset Zoo in Qlib, we use two recommendation datasets: Alpha158 and Alpha360, the constituents of CSI300 in China stock market data [3]. 158 and 360 represent the different number of pre-calculated alpha factors, which can explain and predict future asset returns. We follow the temporal order (avoid the problem of future information leakage) to split data in training (from 01/01/2008 to 12/31/2014), validation (from 01/01/2015, 12/31/2016), and testing (from 01/01/2017 to 08/01/2020). Note that the extra splitting gap of return, i.e., (Close[-2]/Close[-1])−1 [4] is intentionally introduced to avoid the data leakage problem in the daily-frequency dataset.

For cryptocurrencies, we use the high-frequency BTC/USDT trading pair. Each record in this dataset corresponds to one market snapshot, which is captured for approximately every 0.1 second. The training samples used in the experiments come from 7 consecutive trading days (from 01/03/2021 to 07/03/2021), with a total number of 10 million. The validation and testing samples come from the following 7 trading days (from 08/03/2021 to 10/03/2021 and from 11/03/2021 to 14/03/2021). We use the same technical and limit-order book factors to calculate input features as ETFs introduced in Sec. V-B1.

2) Models:
We compare LARA with the following baselines:
- XGBoost [37], LightGBM [27], and CatBoost [38] are non-linear models based on gradient boosting trees.
- MLP is a non-linear model based on neural networks.
- Linear is a linear regression model.
- LSTM [39] is the vanilla LSTM model, which obtains a sequential embedding; and then an FC layer is used to make the final prediction of return.
- GRU [40] is an extended version of LSTM, which has a forget gating mechanism to control the information flow.
- ALSTM [41] adds an external attention layer into the vanilla model to adaptively aggregate hidden states’ information of previous timestamps.
- GATs [42] utilizes the Graph Neural Networks (GNNs) to model the relationship between different stocks, and the attention scheme is incorporated into GNNs.
- SFM [10] redesigns the recurrent neural networks by decomposing hidden states into multiple frequency components to model multi-frequency trading patterns.
- TFT [43] introduces Deep Momentum Networks to simultaneously learn both trend estimation and position sizing

3CSI 300 Index consists of the 300 largest and most liquid A-share stocks, which aims to reflect the overall performance of China A-share market. More information can be found at http://www.csindex.com.cn/en/indices/index-detail/000300.

4 $[-x]$ refers to the closing price of the next $x$ consecutive days.
### Table IV
**Quantitative comparisons among different methods on the China’s A-share market.** - means that it is not implemented in Qlib. **Best results are in bold.** /-/ means results of Alpha158 / results of Alpha360.

| Methods               | Precision(%) | Win-Loss Ratio     | Average Return     | #Transactions |
|-----------------------|--------------|--------------------|--------------------|---------------|
| XGBoost               | 11.1 / 53.3  | 1.182 / 1.138      | 0.00104 / 0.00522  | 1000          |
| LightGBM              | 55.0 / 54.0  | 1.331 / 1.235      | 0.00726 / 0.00538  | 1000          |
| CatBoost              | 4.0 / 55.9   | 1.076 / 1.258      | 0.00007 / 0.00746  | 1000          |
| MLP                   | 49.9 / 51.1  | 1.193 / 1.182      | 0.00302 / 0.00387  | 1000          |
| Linear                | 45.5 / 48.5  | 1.209 / 1.038      | 0.00433 / 0.00118  | 1000          |
| LSTM                  | 55.0 / 53.2  | 1.106 / 1.200      | 0.00553 / 0.00462  | 1000          |
| GRU                   | 51.3 / 50.7  | 1.114 / 1.254      | 0.00302 / 0.00429  | 1000          |
| ALSTM                 | 51.9 / 49.9  | 1.133 / 1.110      | 0.00324 / 0.00262  | 1000          |
| GATs                  | 52.7 / 52.2  | 1.237 / 1.134      | 0.00626 / 0.00493  | 1000          |
| SFM                   | - / 54.3     | - / 1.110          | - / 0.00563        | 1000          |
| TFT                   | 50.7 / -     | 1.184 / -          | - / 0.00392        | 1000          |
| TabNet                | 51.8 / 50.3  | 1.299 / 1.146      | 0.00514 / 0.00283  | 1000          |
| DoubleEnsemble        | 14.4 / 54.0  | 1.379 / 1.225      | 0.00223 / 0.00575  | 1000          |
| LARA                  | 56.6 / 51.4  | 1.142 / 1.031      | 0.00527 / 0.00154  | 1000          |
| + LA-Attention        | 55.2 / 52.8  | 1.038 / 1.152      | 0.00353 / 0.00271  | 1000          |
| + LA-Attention + RA-Labeling | 59.1 / 56.0 | 1.274 / 1.275 | 0.00779 / 0.00546  | 1000          |

### Table V
**Quantitative comparisons among different methods on OKEx.** **Best results are in bold.**

| Methods               | Precision(%) | Win-Loss Ratio     | Average Return     | #Transactions |
|-----------------------|--------------|--------------------|--------------------|---------------|
| XGBoost               | 53.3         | 0.678              | -3.0E-5            | 1000          |
| LightGBM              | 51.0         | 0.890              | 1.4E-5             | 1000          |
| Linear                | 48.1         | 0.927              | 3.4E-5             | 1000          |
| LSTM                  | 43.8         | 1.053              | 1.9E-5             | 1000          |
| GRU                   | 44.4         | 1.013              | 3.7E-5             | 1000          |
| ALSTM                 | 47.9         | 0.933              | 5.9E-5             | 1000          |
| TabNet                | 51.0         | 0.890              | 1.4E-5             | 1000          |
| LARA                  | 51.2         | 0.826              | 9.5E-5             | 1000          |
| + LA-Attention        | 56.2         | 1.034              | 1.4E-4             | 1000          |
| + LA-Attention + RA-Labeling | 57.8 | 1.059 | 1.5E-4 | 1000 |

In a data-driven manner.

- **TabNet [44]** is a deep tabular data learning architecture, which uses sequential attention to choose which features to reason from at each decision step.
- **Double Ensemble [11]** proposes an ensemble framework leveraging learning trajectory based sample reweighting and shuffling based feature selection.
- **TCTS [45]** introduces a learnable scheduler to sequence learning, which can adaptively select auxiliary tasks with the main task.

### 3) Experimental Results:

Results on the China’s A-share stock market shown in Table IV, LARA obtains 59.1% precision and outperforms the baseline models by up to 4.1% in the Alpha158 dataset. For the average return index, our method is slightly better than (in the Alpha158 dataset) and on par with (in the Alpha360 dataset) several deep learning competitors under the 1000 #Transactions with the top predicted probability. We obtain the same results on cryptocurrencies shown in Table V. They all suggest the effectiveness of our proposed method on the real-world markets executed on the Qlib platform.

In Fig. 10, we identify the top three deep learning models with the highest precision in Table IV on the Qlib platform, i.e., LightGBM, LSTM, and GATs. For each method, we select the top 200 signals with the highest predicted probability value in each quarter and perform the t-statistical test of Precision and Average Return between LARA and the corresponding method quarterly (significance level \( \alpha \) equals to 0.05). If the curve is above the dotted red line, it represents that LARA is significantly better than the corresponding model, and vice versa. We can empirically find that from 2019-q1 to 2020-q2,
LARA steadily outperforms the baseline deep learning models. From 2017-q1 to 2019-q1, LARA is on par with the baseline models. The reason could be attributed to violent fluctuation of assets price during this period [46].

In Fig. 11 we plot the trade distribution of LARA in the China’s A-share market and the corresponding index price. We can see more clearly that LARA opens more positions when the index price fluctuates sharply, which also meets our expectation that there will be more opportunities when the market is volatile. These results further demonstrate that LARA can be used in real-world complex investments to pick up reliable trading opportunities.

VI. RELATED WORK

Price movement forecasting. With the advance of deep learning, there are two main research threads in price movement forecasting. The first focuses on introducing new financial data sources into predictors and enhancing feature engineering (e.g., [9], [14], [30], [31], [47]–[49]). Zheng et al. [9] used sentiment analysis to extract useful information from multiple textual data sources. Li et al. [14] leveraged the repositories of investment behaviors within mutual fund portfolio data and the cross effect among involved assets to predict price movement. Besides, there also exists much literature (e.g., [14], [31]) studying new methods to construct stationary features for financial data that can be applied to deep learning methods effectively. The second seeks to construct well-designed prediction models to achieve more accurate price prediction (e.g., [10]–[13], [15], [50]–[52]). Zhang et al. [11] proposed a new ensemble method based on sample reweighting and feature selection for financial data analysis. Xu et al. [15] developed an adaptive regularized model for unexpected revenue prediction. Zhang et al. [10] proposed the state frequency memory recurrent networks for stock price prediction. Wen et al. [50] developed an effective algorithm for separating complex time series components of the financial data.

Reweighting/relabeling. There is a large body of literature on reweighting/relabelling methods to tackle the problem of data imbalance and the non-IID (independent and identically distributed) data generation process. Sample reweighting—assigning higher weights to the ‘harder’ examples with the higher loss—has been widely used in [36], [53], [54]. Class reweighting is another typical method to correct the underestimation of minority classes with few data points [55]. Much effort has also been devoted to the sampling algorithms to overcome the data imbalance, such as SMOTE [56], and ADASYN [57]. As for the relabelling method, [58], [59] uniformly change the label to other classes with a constant flip probability, and the trained models appear to be more resistant to the label noise. In contrast, our proposed method adaptive refined labeling is designed to adaptively refine the similar samples with opposite labels to boost the performance of predictors in the quantitative trading scenarios.

VII. CONCLUSION

In this paper, we study the problem of price movement forecasting and present the LARA (Locality-Aware Attention and Adaptive Refined Labeling) framework. In LARA, we propose the LA-Attention to extract potentially profitable samples and the novel RA-Labeling to reset their labels adaptively. We demonstrate its superior performance over traditional time-series analysis and a set of machine learning based competitors on three real-world financial markets: ETFs, the China’s A-share stock market, and the cryptocurrency market. Besides, we also illustrate how each component works by extensive ablation studies. Extensive experiments demonstrate that LARA indeed captures more reliable trading opportunities. Even though we have achieved superior performance compared with a set of competitors. We largely expect our work to extend price movement forecasting to more realistic scenarios with complex trading environments.
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A. Hyper-Parameters Settings

For the reproducibility of our proposed LARA framework, we describe the hyper-parameter settings in detail here.

**Random Seeds.** We conduct each experiment in the main text with 5 different seeds as shown below. We sample the equal number of positive and negative data points before the training phase. However, in some special cases, these sampled data points may not satisfy the positive semi-definite property of the (squared) Mahalanobis distance matrix. Hence, we use some different seeds for each ETF to satisfy the above property:

- 159915.SZ: 1, 2, 3, 4, 5
- 512480.SH: 1, 2, 3, 4, 5
- 512880.SH: 1, 2, 8, 9, 11
- 515050.SH: 3, 5, 7, 8, 9

**Hyper-Parameters.** In order to compare different methods, we first search hyper-parameters on the validation set, whose search space is listed in Sec. V-B1, and then select the best hyper-parameters based on their performance. We list the detailed values of $K$ in K-Neighbor, $R$ in R-Neighbor, $k$ in RA-Labeling method, and $r$ in RA-Labeling method in Table VI.

| ETF          | K-Neighbor/ R-Neighbor | $K$  | $R$  | $k$  | $r$  | Combining method |
|--------------|------------------------|------|------|------|------|------------------|
| Positive Cases  
159915.SZ   | K-Neighbor             | 150  | -    | 7    | 0.05 | vote             |
|             | R-Neighbor             | 90   | 100  | 9    | 0.04 | vote             |
|             | R-Neighbor             | 150  | 50   | 7    | 0.07 | vote             |
|             | K-Neighbor             | 120  | -    | 9    | 0.05 | vote             |
| Negative Cases  
159915.SZ   | K-Neighbor             | 100  | -    | 9    | 0.07 | vote             |
|             | R-Neighbor             | 150  | 30   | 9    | 0.03 | vote             |
|             | K-Neighbor             | 150  | -    | 9    | 0.10 | vote             |

B. Masked Attention Scheme

We use a more intuitive example to further explain the masked attention scheme in Fig. 12. Even though the optimal linear classifier $y = x$ (omitting the bias term for convenience) is determined to classify samples drawn from $\mathcal{N}((-2, 2), 4I_2)$ and $\mathcal{N}((2, -2), 4I_2)$, the actual classifier built over the sampled datasets deviates from $y = x$ owing to the insufficient sample size and noise, especially in the middle region where positive and negative samples are mixed together. Intuitively, extracting samples with high $p_x$ in the blue (positive) and red (negative) regions with less noise and training classifiers over them can generate a more robust predictor. As a result, the generated predictor is closer to the optimal line $y = x$, and not susceptible to the samples in the area where positive and negative samples are mixed together. In the testing phase, we merely focus on the samples with high $p_x$, which are easy to be distinguished with respect to the learned predictor. Hence, the masked attention scheme, which trains and predicts on the samples with high $p_x$ in the blue and red regions, is more robust to the deviation of the learned decision boundary and can generate real profitable signals in the quantitative trading scenarios.

Fig. 12. The intuitive example for illustrating the masked attention scheme. Sample 200 data points from $\mathcal{N}((-2, 2), 4I_2)$ and $\mathcal{N}((2, -2), 4I_2)$ as positive and negative training samples, respectively. Testing samples are drawn from the same distribution. The blue region (upper left) stands for the area within positive samples with high $p_x$. The red region (lower right) stands for the area within negative samples with high $p_x$. For a linear classifier $y = w \cdot x$, the red dotted line represents the optimal solution and other solutions deviate from the optimal one (mainly located in green) due to insufficient sample size and noise.

This conclusion is trivial and intuitive, and the rigorous mathematical proof can refer to [60].