Market Volatility Prediction Based on Long- and Short-Term Memory Retrieval Architectures

Jie Yuan**
Iowa State University
Ames, USA
jieyuan@iastate.edu

Zhu Zhang*
Iowa State University
Ames, USA
zhuzhang@iastate.edu

ABSTRACT

Predicting market volatility is a critical issue in financial market research and practice. Moreover, in natural language processing, how to effectively leverage long- and short-term event sequences to predict market volatility is still a challenge. Especially, applying traditional recurrent neural networks (RNNs) on an extremely long event sequence is infeasible due to the high time complexity and the limited capability of the memory units in RNNs. In this paper, we propose a new deep neural network-based architecture named Long- and Short-term Memory Retrieval (LSMR) architecture to forecast short-term and mid-term volatility. LSMR architecture consists of three separate encoders, a query extractor, a long-term memory retriever, and a volatility predictor. The query extractor and the long-term memory retriever compose a long-term memory retrieval mechanism that enables the LSMR to handle the extremely long event sequences. Experiments on our novel news dataset demonstrate the superior performance of our proposed models in predicting highly volatile scenarios, compared to existing methods in the literature.

CCS CONCEPTS

• **Applied computing** → **Economics**; • **Computing methodologies** → **Neural networks**.

KEYWORDS

market volatility, long-term memory, short-term memory, retrieval, LSTM, RIMs

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1 INTRODUCTION

In finance, volatility is the degree of variation of a trading price series over time [1]. Market volatility is generally considered as a vital metric to evaluate the level of risk, and thus it plays a critical

*Both authors contributed equally to this research.

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rule in assessing the stock market risk and the pricing of derivative securities [21]. However, one of the significant challenges for the volatility prediction is the high stochasticity of the market.

Throughout the past several decades, a large number of research studies formulate volatility prediction as time series forecasting using historical data [7, 11, 17]. However, in reality, one of the significant stochasticity sources of the market is unstructured textual data, such as public news, financial reports, and social media [14, 18, 20].

With recent advances in natural language processing (NLP) and deep learning, it has become possible to leverage unstructured textual data to predict market volatility. A large number of current textual-based models only leverage short-term information (e.g., several days' news or tweets) to predict the stock movement [6, 20, 22]; they ignore the long-term dependencies existing in textual data. For instance, a previous event that happened several months or years ago may have a latent relationship with today's stock. Several works leverage both short-term and long-term events to predict stock movements (classification task) [5, 6]. However, they might lose part of the long-term temporal information by using convolutional neural networks to process sequential data.

Distinct from the previous works, we formulate market volatility prediction as a regression task and seek to build on recurrent neural networks (RNNs) to further explore the utility of long-term memory for short-term and mid-term volatility forecasting. Nevertheless, one issue is that the RNNs will lose long-term information if the time series is exceptionally long. For example, suppose there is 30 news in one day, and we want to leverage the previous 90 days' news to make a prediction. The length of time series will be 2700; it is far more computationally expensive and infeasible to apply RNN on such a long time series. To alleviate this issue and capture the long-term information efficiently meanwhile taking advantage of the short-term information, we propose a Long- and Short-term Memory Retrieval (LSMR) architecture in which a long-term memory retrieval mechanism compresses long-term memory into K sub-sequences by retrieving from long-term memory and the K sub-sequences not only consist of the essential long-term information but relatively short. Thus, it becomes feasible that RNNs can capture long-term information from extremely long memory by performing RNNs on the K event sub-sequences.

Moreover, although RNNs, such as LSTM [12] and GRU [3], achieve great success on time series tasks, it is hard for one recurrent cell to capture the global dynamics (temporal patterns) and sequence information. Recently, [10] introduce a new neural recurrent model, called Recurrent Independent Mechanisms (RIMs), which performs better than LSTM [12] on multiple sequential tasks;

the experiments show that RIMs can capture distinct temporal patterns in the data and improve generalization to settings where these patterns change. In this paper, to leverage and validate the power of RIMs, we apply RIMs and LSTM on volatility prediction tasks and compare the performances between RIMs and LSTM.

The contributions of this paper can be summarized as follows:

- We build a new news dataset from the Wall Street Journal (WSJ) and leverage it to predict the market volatility.
- We propose a long- and short-term memory retrieval (LSMR) architecture for the short-term and long-term volatility forecasting, and our LSMR-based models achieve superior performance in predicting highly volatile scenarios.
- To the best of our knowledge, it is the first time applying RIMs on the textual dataset for the volatility prediction, and indeed the experimental results show the potential capability of RIMs on processing the textual data.

2 RELATED WORK

One branch of research on forecasting market volatility is based on historical pricing data [8] [2] [15]. Due to the success of deep neural networks in other related domains, [17] propose a neural stochastic volatility model (NSVM) for volatility estimation and prediction. It is a stochastic recurrent neural network framework that can formulate the temporal dynamics of volatility over time. The NSVM only relies on the historical pricing data without incorporating additional sources of volatility information.

Another branch to predict market volatility is to take advantage of natural language resources, such as tweets, financial news, etc. [6] extract events from news text, model the influence of long, short term events by using conventional neural networks, and predict the stock price movements. [5] predict the stock price movement by adopting Open IE technology. [13] intimate the process of human processing chaotic online news and design a hybrid attention network to predict the stock trend. Most recently, [20] propose a model, called *StockNet*, to predict stock movement from tweets and historical prices by introducing a recurrent, continuous latent variable for better simulating stochastic. The above models are used to predict the stock price movements (classification task); in contrast, our goal is to alleviate a regression problem.

Recurrent neural networks, such as LSTM [12] and GRU [3], have been widely used in forecasting time series, however, a single recurrent cell cannot capture global sequential information. Recently, [10] propose Recurrent Independent Mechanisms (RIMs), which is a new recurrent architecture in which multiple RIMs can be active, interact, and share information. Each RIM has its independent dynamics operating by default, and occasionally to interact with other relevant RIMs and with selected elements of the encoded input. Unlike the gating mechanism applied to the inputs in the RNNs, RIMs control each module's input.

3 BACKGROUND

In this section, we introduce the architecture of LSTM and Recurrent Independent Mechanisms (RIMs).

3.1 LSTM

LSTM [12] is one of the prevalent recurrent neural models due to the long-term and short-term memory mechanism. It uses a cell state to maintain long-term memory, and the cell state C at time step t is updated in terms of an input gate i_t and a forget gate f_t .

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (1)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (2)$$

$$\hat{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (3)$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \hat{C}_t \quad (4)$$

where h_{t-1} is the hidden state at time step $t-1$, and x_t is the input at time step t . W_f , W_i , W_C , b_f , b_i , and b_C are model parameters. For the short-term memory, at time step t , an output gate o_t controls the short-term memory.

$$o_t = \sigma(W_o [h_{t-1}, x_t] + b_o) \quad (5)$$

$$h_t = o_t \cdot \tanh(C_t) \quad (6)$$

where W_o and b_o are model parameters.

However, if the input is hugely complex, one LSTM can not capture all the latent dynamics in the data. Therefore, [10] present that multiple independent recurrent units catch distinct patterns and communicate sparingly is a better mechanism to model dynamics.

Figure 1: One step of Recurrent Independent Mechanisms (RIMs).

3.2 Recurrent Independent Mechanisms (RIMs)

In [10], a dynamic system can be composed of K subsystems, which are denoted as Recurrent Independent Mechanisms (RIMs). RIMs operate with nearly independent transition dynamics, communicate only sparingly through the bottleneck of attention, and are only updated at time steps where they are most relevant. Each RIM, which can be implemented by using an LSTM or a GRU, is recurrent and has distinct functions that are learned automatically from data. For one single step of RIMs, it contains four stages: (1) Each RIM produces a query; (2) An attention-based competition mechanism is applied to select which RIMs to activate; (3) Activated RIMs follow their default transition dynamics while non-activated RIMs remain

unchanged; (4) the RIMs sparsely communicate information with each other in terms of attention. A single step of RIMs is shown in Figure 1.

Produce a query (Stage 1): The state of RIM k at time step t can be denoted as $h_{t,k}$, where $t = 1 \dots T$, and then $Q_k = h_{t,k} W_k^q$ is the query of RIM k , where W_k^q is a weight matrix which maps from the RIM's hidden state to its queries.

Competition mechanism (Stage 2): The goal of the competition mechanism is to dynamically select those RIMs for which the current input is relevant. The input at time t is represented as x_t . Then, x_t is concatenated with a row full of zeros $\emptyset$ to obtain X ,

$$X = x_t \oplus \emptyset \quad (7)$$

Then, the attention score for RIM k is defined as

$$a_k^{in} = \text{softmax}\left(\frac{Q_k K^T}{\sqrt{d_e}}\right), k \in 1 \dots K \quad (8)$$

where $K = X W^k$, W^k is a weight matrix; d_e is the dimension of each key. Based on the softmax values, selecting top k_A RIMs with the highest attention score (out of the total K RIMs) to be activated and call them set S_t . Then, the new input for RIMs in S_t is

$$A_k^{in} = a_k^{in} X W^v \quad (9)$$

where W^v is a weight matrix; in practice, they use a multi-head attention technique.

Independent RIM dynamics (Stage 3): Stage 3 is to update the hidden states of individual RIMs. The hidden states of RIMs that the independent dynamics are applied are represented as $\tilde{h}_{t,k}$. For the RIMs that are not activated, the hidden states remain unchanged,

$$\tilde{h}_{t,k} = h_{t,k}, \forall k \notin S_t \quad (10)$$

The active RIMs are updated by

$$\tilde{h}_{t,k} = \text{LSTM}(h_{t,k}, A_k^{in}; \theta_k^D), \forall k \in S_t \quad (11)$$

where θ_k^D is the parameter of RIM k , $k \in S_t$. Each LSTM (RIM) has parameters θ_k , which are shared across all time steps.

Communication between RIMs (Stage 4): The attention mechanism allows the sharing of information among the RIMs, specifically the activated RIMs, can be read from all other RIMs (activated or not).

$$Q_{t,k} = \tilde{W}_k^q \tilde{h}_{t,k}, \forall k \in S_t \quad (12)$$

$$K_{t,k} = \tilde{W}_k^e \tilde{h}_{t,k}, \forall k \quad (13)$$

$$V_{t,k} = \tilde{W}_k^v \tilde{h}_{t,k}, \forall k \quad (14)$$

$$h_{t+1,k} = \text{softmax}\left(\frac{Q_{t,k}(K_{t,:}^T)}{\sqrt{d_e}} V_{t,:}\right) + \tilde{h}_{t,k}, \forall k \in S_t \quad (15)$$

where $\tilde{W}_k^q$, $\tilde{W}_k^e$, and $\tilde{W}_k^v$ are weight matrices.

4 MODEL FOR VOLATILITY PREDICTION

In this section, we first formulate the problem of volatility prediction. Then, we introduce the long- and short-term memory retrieval (LSMR) architecture, which is composed of five components: Sentence encoder, Short-term event sequence encoder, Query extractor, Long-term memory retriever, Long-term event sequence encoder, and volatility predictor. The overall architecture is shown in Fig 2.

4.1 Problem Formulation

We aim at predicting the volatility of the S&P 500 (SP) index, $SPVt1$, and $SPVt22$, at stock market close time t on a target trading day d based on news titles in the Wall Street Journal. The volatility (Vt) is defined as the difference between anchor day's high and low price divide the average of anchor day's open and close prices.

The $SPVt1$ and $SPVt22$ are defined as follow:

$$SPVt1 = \frac{\text{Max}(\text{PriceHigh}_{t:t+1}) - \text{Min}(\text{PriceLow}_{t:t+1})}{\text{Avg}(\text{PriceClose}_{t-1}, \text{PriceClose}_{t+1})} \quad (16)$$

$$SPVt22 = \frac{\text{Max}(\text{PriceHigh}_{t:t+22}) - \text{Min}(\text{PriceLow}_{t:t+22})}{\text{Avg}(\text{PriceClose}_{t-1}, \text{PriceClose}_{t+22})} \quad (17)$$

Formally, the problem of volatility prediction can be formalized as follows: given a target trading day d , a stock market close time t_d on d and a time window W_d , where $W_d = [t_d - \Delta h, t_d - 1 \text{ hour}]$ and Δh is a fixed lag size. Then, a short-term memory can be denoted as $M_{short} = W_d$, and a long-term memory can be represented as $M_{long} = [W_{d-1 \text{ day}}, W_{d-2 \text{ days}}, \dots, W_{d-n \text{ days}}]$. In each time window W_d , there are N news titles in W_d , and all titles in $W_d = [NT_1, NT_2, \dots, NT_N]$, and all titles in W_d are sorted in accordance with Unix time. For each news title NT_n , $n \in [1, N]$, it contains L tokens TK , $NT_n = [TK_1, TK_2, \dots, TK_L]$. Our goal is to use the long-term and the short term memory to predict $SPVt_1$ and $SPVt_{22}$.

4.2 Model Components

Sentence encoder: We take advantage of pre-trained BERT¹ [4] [19] to tokenize and encode news title NT_n to a sequence of token embedding $NT_n^E = [TK_1^E, TK_2^E, \dots, TK_L^E]$, where $TK_l^E \in \mathbb{R}^{1 \times d_m}$, $l \in [1, L]$. We feed news title into pre-trained BERT and extract the last second hidden layer and then average the extracted layer to construct a news title vector $NT_n^{BERT} \in \mathbb{R}^{1 \times d_m}$. Then, the short-term memory can be denoted as $M_{short}^E = W_d^E$, where

$$W_d^E = [NT_1^{BERT}, NT_2^{BERT}, \dots, NT_N^{BERT}] \quad (18)$$

The long-term memory can be represented as

$$M_{long}^E = [W_{d-1 \text{ day}}^E, W_{d-2 \text{ days}}^E, \dots, W_{d-n \text{ days}}^E] \quad (19)$$

Short-term event sequence encoder: To capture the short-term information; the M_{short}^E is encoded by using recurrent neural network RNN (LSTM or RIMs):

$$h_{short} = \text{RNN}(M_{short}^E) \quad (20)$$

Since traditional RNNs can not deal with extremely long time-series efficiently, we alleviate this issue by proposing a long-term memory retrieval mechanism. First, we leverage **query extractor** to extract the k significant events (news titles) in terms of attention

¹https://s3.amazonaws.com/models.huggingface.co/bert/bert-base-uncased-pytorch_model.bin

Figure 2: The Long- and Short-term Memory Retrieval (LSMR) architecture.

scores. Then, we perform **long-term memory retriever** on long-term memory and return K event (sentences) sub-sequences with length M , which compresses long-term information into K relative short event sequences. By leveraging the long-term memory retrieval mechanism, RNNs can be applied to K event sub-sequences to efficiently capture long-term information.

Query extractor: Not all the news in W_d has a high relationship with volatility, thus we aim to find the K most significant event in W_d by using a self-attention mechanism. We extract K titles as queries from W_d , which have high self-attention scores:

$$raw_score = \tanh(W_2 \tanh(W_1 (M_{short}^E)^T) + b_1) + b_2 \quad (21)$$

$$att_score = \text{softmax}(raw_score) \quad (22)$$

where W_1, W_2, b_1 and b_2 are model parameters. $M_{short}^E \in \mathbb{R}^{N \times d_m}$ represents embedded short-term memory. $raw_score, att_score \in \mathbb{R}^{1 \times N}$.

$$K - queries = \{NT_i^{Embed} | i \in \text{topK_index}(att_score)\} \quad (23)$$

where $\text{topK_index}(att_score)$ returns the indices of top K NT_i^{Embed} which have high attention scores.

Long-term memory retriever: For each query out of K queries, we use the query to retrieve a time sequences of titles from long-term memory. The intuition is that each query represents a significant event in W_d , we can find a similar event that happened in history, and there is an underlying pattern that is highly related to the current market. We leverage bi-linear matrix to mine the underlying long-term pattern, and the long-term memory retriever is defined as:

$$scores_k = NT_k^{Embed} W_3 (M_{Long}^E)^T, NT_k^{Embed} \in K - queries \quad (24)$$

$$seq_att_scores_k = \text{softmax}(scores_k), k \in K \quad (25)$$

where NT_k^{Embed} is k_{th} query in K -queries, $W_3 \in \mathbb{R}^{d_m \times d_m}$ is a bilinear matrix. Then, for each query $NT_k^{Embed} \in K - queries$, we

can extract a time sequence with length M from M_{Long} .

$$sequences_k = \{NT_i^{Embed} | i \in \text{topK_index}_{temp}(seq_att_scores)\} \quad (26)$$

where topK_index_{temp} returns a sentence (news title) sequence in temporal order; $sequences_k \in \mathbb{R}^{M \times d_m}$.

Long-term event sequence encoder: The long-term retriever returns K event sequences; then, we perform RNN (LSTM or RIMs) on K event sequences:

$$h_k = RNN(sequences_k), k \in [1, \dots, K] \quad (27)$$

Volatility predictor: We leverage the concatenation of the K encoded long-term event sequences $[h_1; h_2; \dots; h_K]$ and the encoded short-term event sequence h_{short} to predict the volatility:

$$Y = W_5 (W_4 [h_1; h_2; \dots; h_K; h_{short}] + b_4) + b_5 \quad (28)$$

Where W_4, W_5, b_4 and b_5 are model parameters, Y is the volatility to predict, $[h_1; h_2; \dots; h_K; h_{short}]$ is the concatenation of K hidden layers and h_{short} .

Finally, by using different recurrent unit (LSTM or RIMs), we obtain two models: **Long- and Short-term Memory Retrieval LSTM (LSMR-LSTM)** and **Long- and Short-term Memory Retrieval RIMs (LSMR-RIMs)**.

5 EXPERIMENTS

In this section, we introduce our dataset for our application and evaluation metrics for assessing the performance of different models. Several baselines for volatility prediction are also presented.

5.1 Data Collection

In our experiments, we create a novel dataset from the Wall Street News. We use the volatility of S&P 500 (SP) index from 01/02/2001 to 03/13/2018 as our prediction target. We split them temporally, and 2,898 days from 01/02/2001 to 07/10/2012 are for training, 723

days from 07/11/2012 to 05/29/2015 are for validation, and 702 days from 06/01/2015 to 03/13/2018 are for the test. Our task is to use the news to predict market volatility, and Wall Street Journal (WSJ) is a U.S. finance-focused newspaper, which has millions of news concerning the business. So, we crawl all the news in WSJ archive² from 2001 to 2018 and finally obtain 699,290 news.

We observe that not all the news published in the WSJ is highly related to business. There is much noise in our crawled news dataset, and we also observe that all the news contains a *article_type* tag indicted which type of the news belongs to. We pre-process news dataset by computing the word cosine similarity between *article_type* with four types, *Business*, *Economy*, *Stock* and *Market* separately. *article_type* and four types are converted to word embedding pre-trained by Glove³. Then for each news, comparing the sum of four similarity scores with a threshold (the threshold is set to be 2.0), if the sum of similarity scores is less than the threshold, the news will be removed from the dataset. After preprocessing, 606,523 news is removed, and our final dataset has 92,767 news.

5.2 Training setup

In our experiments, we predefined the time lag $\Delta h = 25$, the size of long-term memory $n = 30$ or 90 , the number of news titles $N = 30$ and the title length $L = 20$. For the LSTM-based models, the dimension of the hidden layer of LSTM is 200, and we use two layers in LSTM. We use Xavier uniform initializer [9] to initialize parameters in LSTM. For RIMs-based models, the number of RIMs $K = 4$, and the number of activated RIMs $K_A = 2$. The dimension of the hidden state of individual RIM is 64. For the LSMR architecture, the number of queries $K = 3$ in the query extractor component; the sequence length $M = 20$ in long-term memory retriever. We train all the models with an Adam optimizer [16] with an initializing learning rate of 10^{-4} , and the dropout rate is set to 0.2. The batch size is 32, the dimension of token embedding $d_m = 768$, and the dimension of a fully connected layer is 200. All the models run five times, and the hyper-parameters are tweaked on the validation dataset.

5.3 Evaluation Metrics for Volatility Prediction

Firstly, to evaluate the performance of our models and baselines on volatility prediction, we use MAPE, MAE, MSE (Errors) as evaluation metrics (lower errors are better).

Except that, in the financial field, investors care more about spikes (high volatility), so we classify target variables into two classes and convert the target variable $Y \geq \mu + \sigma$ to positive class and $Y < \mu + \sigma$ to negative class, where μ is the mean of the target variable, and σ is the standard error of the target variable. Then, taking advantage of Precision, Recall, and F1-score (higher values are better) as metrics to evaluate the models on predicting spikes.

It should be noticed that the goals of the two sets of metrics are different. Errors are used to measure how well models fit the target variables, while Precision, Recall, and F1-value (P/R/F) are employed to evaluate how successful the models on predicting spikes. High P/R/F means more spikes can be predicted, meanwhile

it will results in high Errors as well. In this paper, we pay more attention to the spikes prediction (P/R/F).

The definition of MAPE, MAE, MSE, Precision, Recall, and F1-value are as follows:

$$MAPE(y, \hat{y}) = \frac{100\%}{N} \sum_{i=1}^N \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (29)$$

$$MAE(y, \hat{y}) = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (30)$$

$$MSE(y, \hat{y}) = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (31)$$

where y_i is the actual value, $\hat{y}_i$ is the forecast value. N is the number of samples.

$$Precision = \frac{TP}{TP + FP} \quad (32)$$

where TP denotes True Positive. If $Y \geq \mu + \sigma$ and $\hat{Y} \geq \mu + \sigma$, data point will be classified to TP. FP denotes False Positive, if $Y < \mu + \sigma$ and $\hat{Y} \geq \mu + \sigma$, data point will be classified to FP.

$$Recall = \frac{TP}{TP + FN} \quad (33)$$

where FN denotes False Negative. If $Y \geq \mu + \sigma$ and $\hat{Y} < \mu + \sigma$, the data point will be classified to FN.

$$F1 - value = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \quad (34)$$

F1-value is calculated based on Precision and Recall.

5.4 Proposed Models and Baselines

To make a detailed analysis of the utility of long-term memory and short-term memory, we construct two short-term based models and two long-term based models.

For short-term based models, we preprocess the input by splitting W_d into 24 segments, and the time range of one segment is one hour. In each segment, the number of news titles is five, and the length of titles (the number of tokens) is 20.

- **Nested Attention Short-term Memory LSTM (NASM-LSTM):** we introduce a nested attention mechanism to firstly aggregate the tokens weighted by assigned word-level attention values, then compute the weighted sum of sentences in the individual segment by using sentence-level attention values. After that, we obtain a temporal sequence with length 24 and apply LSTM on it. Finally, the last hidden layer of LSTM is feed into a fully connected layer and a linear layer to make predictions.
- **Nested Attention Short-term Memory RIMs (NASM-RIMs):** The LSTM in NASM-LSTM is replaced with RIMs.

For long-term based models, the inputs are the same as the LSMR.

- **Long-term Memory Retrieval LSTM (LMR-LSTM):** the model only has sentence encoder, query extractor, long-term memory retriever and volatility predictor four component. In the volatility predictor component, the LSTM applies to retrieved sequences.
- **Long-term Memory Retrieval RIMs (LMR-RIMs):** The LSTM in LMR-LSTM is replaced with RIMs.

²<https://www.wsj.com/news/archive/>

³<http://nlp.stanford.edu/data/glove.42B.300d.zip>

Models	SPVt1 Prediction						SPVt22 Prediction					
	MAPE	MAE	MSE	Precision	Recall	F1-value	MAPE	MAE	MSE	Precision	Recall	F1-value
NSVM	128.544	0.010401	0.000145	0.106	0.021	0.035	92.844	0.033257	0.001332	0.000	0.000	0.000
StockNet	58.999	0.006608	0.000102	0.000	0.000	0.000	49.744	0.023050	0.000889	0.100	0.002	0.003
Mean Baseline	131.332	0.010584	0.000148	0.000	0.000	0.000	92.817	0.033242	0.001330	0.000	0.000	0.000
NASM-LSTM	81.081	0.007735	0.000112	0.079	0.012	0.020	79.756	0.030662	0.001433	0.180	0.170	0.174
LMR-LSTM(30)	121.761	0.010733	0.000188	0.099	0.198	0.131	92.174	0.033735	0.001565	0.175	0.253	0.197
LSMR-LSTM(30)	117.092	0.010008	0.000157	0.128	0.205	0.154	81.545	0.031132	0.001339	0.185	0.147	0.143
LMR-LSTM(90)	104.591	0.009630	0.000154	0.113	0.092	0.094	79.033	0.030863	0.001343	0.183	0.138	0.147
LSMR-LSTM(90)	100.505	0.009274	0.000147	0.203	0.162	0.156	67.839	0.028320	0.001234	0.165	0.087	0.089
NASM-RIMs	135.390	0.011073	0.000173	0.139	0.209	0.166	90.919	0.034182	0.001683	0.189	0.283	0.217
LMR-RIMs(30)	148.395	0.013331	0.000290	0.127	0.315	0.180	97.838	0.036651	0.001935	0.185	0.357	0.239
LSMR-RIMs(30)	163.774	0.014468	0.000327	0.119	0.386	0.181	112.315	0.041028	0.002405	0.187	0.503	0.272
LMR-RIMs(90)	151.072	0.013352	0.000292	0.120	0.322	0.174	98.488	0.037008	0.001952	0.183	0.388	0.248
LSMR-RIMs(90)	169.196	0.014992	0.000358	0.122	0.393	0.185	103.940	0.038998	0.002155	0.175	0.408	0.245

Table 1: Performance of baselines and our models to predict the SPVt1 and the SPVt22 on the testing dataset (the size of long-term memory is displayed in parentheses, 30 represents previous 30 days news, 90 represents previous 90 days news; we use boldface to label LSMR-based models).

Moreover, we compare our models with three baselines,

- NSVM [17]: a stochastic recurrent neural network framework which can formulate the temporal dynamics of volatility over time and predict the log-return $x_t = \log(s_t/s_{t-1})$ of actual prices s_t on date t . Different from our model, NSVM is evaluated based on Negative Log-Likelihood (NLL). In order to compare our models with NSVM on predicting the $SPVt_n$, we train the model by multi-task learning. The input is the same as the short-term based models. Since Σ_t^x represents the variance of x_t , $SPVt_n$ represents the volatility of series, it can be regarded as variance as well, so we add another linear layer on the top of Σ_t^x and predict the $SPVt_n$. The joint loss is the sum of MSE and NLL. We predefine the dimensions of observable variables, and the latent variables are the same as in [17].
- StockNet [20]: a model to predict the movement of the stock based on tweets and historical prices. In order to compare the StockNet with our models, we have to modify their architecture: (1) StockNet predicts stock movements based on tweets and historical prices. In contrast, our models predict the volatility only based on news. So, we remove Market Information Encoder(MIE) component in StockNet and directly use our encoded input to replace MIE; (2) Since our models work on the regression problem, however, StockNet is applied on the classification task. We remove the softmax function on the top layer so that the model can predict volatility; (3) The objective function of StockNet contains a likelihood term and a KL term. We replace the likelihood term with Mean Square Error (MSE), so that we can train the modified StockNet successfully. The input is the same as the short-term based models.
- Mean baseline: the mean of all true values in the training and validation dataset is the prediction.

5.5 Experimental Results

Table 1 summarizes the results of the testing dataset in the metrics MAPE, MAE, MSE, Precision, Recall, and F1-value. Although

Figure 3: SPVt1 prediction results of LSMR-RIMs, StockNet, and NSVM on testing dataset visualized.

StockNet achieves the lowest MAPE, MAE, and MSE among all the models on SPVt1 and SPVt22 predictions, part of our proposed models can still beat the other two baselines. Moreover, we found that, in the testing dataset, the mean and standard deviation of SPVt1 is 0.013 and 0.009828; the mean and standard deviation of SPVt22 is 0.052 and 0.029. This means that the variations of SPVt1 and SPVt22 are in a small range. If the predictions fluctuate around the mean, the models can obtain low errors, while they do not successfully fit target variables. In reality, spikes (high volatility) reflect high risks; how well the models predict the spikes are of great practical importance. Under F1-value, we can see that the models based on LSMR architecture perform better than proposed models and baselines (except LSMR-LSTM(30) and LSMR-LSTM(90) on SPVt22 prediction), and all the RIMs-based models outperform

Figure 4: SPVt22 prediction results of LMSR-RIMs, StockNet, and NSVM on testing dataset visualized.

other models, which indeed valid the efficiency of our LSMR architecture and capability of RIMs to capture latent dynamics. In the next section, we will analyze the empirical results in detail.

For visualization, we first randomly selected one run result out of five-run for all models. Then, we plotted the predictions results of LSMR-RIMs(30), StockNet, and NSVM on the testing dataset in Figure 3 and Figure 4. Red lines in all figures are the target variables. As we can see, the predictions of StockNet and NSVM fluctuate in a small range; in contrast, LSMR-RIMs(30) demonstrates the power to predict the spikes. The plots regarding StockNet and NSVM in two figures again valid that low MAPE, MAE, and MSE can not sufficiently demonstrate the ability of models to predict volatility; therefore, it indeed convinces the necessity of leveraging Precision, Recall, and F1-value to evaluate model performances.

6 ANALYSIS

In this section, we analyze the empirical results from the following four aspects based on F1-value: (1) SPVt1 vs. SPVt22; (2) LSMR architecture and models; (3) long-term memory vs. short-term memory; (4) long-term memory size (30 vs. 90 days).

SPVt1 vs. SPVt22: SPVt1 and SPVt22 display the variation of the S&P 500 (SP) index during 1 and 22 trading days after the anchor day separately. Since SPVt1 indicates the variation of the SP index in one day, it fluctuates more heavily than SPVt22, so that intuitively

it is harder than SPVt22 task. The red lines in Figure 3 correspond true SPVt1 in the testing dataset, and the red lines in Figure 4 are true SPVt22 in the testing data. It is obvious that the plot of SPVt22 is smoother than SPVt1. In the testing dataset, for SPVt1, there are 85 out of 702 days whose true values are higher than $\mu + \sigma$; for SPVt22, 120 out of 702 days whose actual values are higher than $\mu + \sigma$. Even though SPVt22 has more spikes than SPVt1 in the testing dataset, our model still can achieve a higher F1-value on the SPVt22 task; it indeed proves SPVt1 is a tougher task.

LSMR architecture and models: In this paper, we propose a Long-term Memory Retrieval (LMR) mechanism to overcome the drawback of RNN on dealing with extremely long event sequences. As shown in Table 1, all of the LMR-based models have higher F1-value than baseline on SPVt1 prediction. For SPVt22 prediction, expect LMR-LSTM(90) is 0.027 lower than NASM-LSTM on F1-value, all the other LMR-based models still outperform short-term models. The results indeed prove that the LMR mechanism can improve the efficiency of RNNs to process long-term memory by extracting event sub-sequences from long-term memory.

By incorporating short-term memory with long-term memory, we present a Long- and Short-term Memory Retrieval (LSMR) architecture, which not only utilizes the long-term memory but also takes the short-term information into account. The results of LSMR-based models are labeled in boldface in Table 1. All the LSMR-based models outperform short-term based, LMR-based models on SPVt1 prediction. For SPVt22 prediction, even though LSMR-LSTM(30)(90) can not beat NASM-LSTM, LMR-LSTM(30)(90), they still perform better than other baselines. Moreover, the LSMR-RIMs(90) and LSMR-RIMs(30) have the highest F1-value on SPVt1 prediction and SPVt22 prediction separately, and both best models are based on the LSMR architecture.

To prove the efficiency of RIMs, we compared LMR-LSTM with LMR-RIMs, LSMR-LSTM with LSMR-RIMs separately. It can be seen from the data in Table 1 that all RIMs-based models perform better than LSTM-based models. It indeed proves that RIMs act independently, and communicate only sparingly through the bottleneck of attention, have the potential to detect and capture more underlying dynamics from data.

Long-term memory vs. short-term memory: In Table 1, all the models utilizing long-term memory achieve higher F1-value than short-term based models (except NASM-RIMs). In order to remove the influence of RIMs, we also compare NASM-RIMs with LMR-RIMs and LSMR-RIMs. The results show that LMR-RIMs and LSMR-RIMs outperform NASM-RIMs, confirming that long-term memory is useful to predict volatility in our tasks.

Long-term memory size (30 vs. 90 days): We conducted experiments about different long-term memory size. Although LSMR-RIMs(90) has the highest F1-value on the SPVt1 prediction task, there is no sufficient evidence to illustrate that 90 days' memory is better than 30 days. However, since 90 days' memory is only the medium-term memory, we will systematically study the exact long-term memory in the future.

7 CONCLUSION AND FUTURE WORK

In this paper, we first build a novel news dataset from the Wall Street Journal (WSJ) for predicting the short-term and mid-term volatility.

Next, we propose a long- and short-term memory retrieval (LSMR) architecture, which efficiently captures long-term information by a long-term memory retrieval mechanism, then applies recurrent neural networks (LSTM or RIMs) to make predictions. Extensive experiments are conducted on the WSJ dataset that exhibit the efficiency of the long-term memory retrieval mechanism to handle extremely long memory, the capability of RIMs to capture dynamics, and the superior performance of our models in predicting highly volatile scenarios.

Our future works include improving the LSMR architecture by introducing reasoning mechanisms, attempting other embedding techniques, systematic study of long-term memory size, and conducting experiments on predicting long-term volatility and comparing the results with short- and mid-term volatility.

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