Improving Stock Movement Prediction with Adversarial Training

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\section*{Abstract}
This paper contributes a new machine learning solution for stock movement prediction, which aims to predict whether the price of a stock will be up or down in the near future. The key novelty is that we propose to employ adversarial training to improve the generalization of a recurrent neural network model. The rationality of adversarial training here is that the input features to stock prediction are typically based on stock price, which is essentially a stochastic variable and continuously changed with time by nature. As such, normal training with stationary price-based features (e.g., the closing price) can easily overfit the data, being insufficient to obtain reliable models. To address this problem, we propose to add perturbations to simulate the stochasticity of continuous price variable, and train the model to work well under small yet intentional perturbations. Extensive experiments on two real-world stock data show that our method outperforms the state-of-the-art solution (Xu and Cohen 2018) with 3.11\% relative improvements on average \textit{w.r.t.} accuracy, verifying the usefulness of adversarial training for stock prediction task. Codes will be made available upon acceptance\textsuperscript{1}.

\section{Introduction}
Stock market is one of the largest financial markets, having reached a total value of 80 trillion dollars in 2018\textsuperscript{2}. Predicting the future status of a stock has always been of great interest to many players in the stock market. While the exact price of a stock is known to be unpredictable (Walczak 2001; Nguyen, Shirai, and Velcin 2015), research efforts have been focused on predicting the stock price movement — e.g., whether the price will be up/down, or the price change exceeds a threshold — which is more achievable than stock price prediction (Pascucci 2011; Adebiyi, Adewumi, and Ayo 2014; Feng et al. 2018; Xu and Cohen 2018).

Stock movement prediction can be addressed as a classification task. After defining the label space and the features to describe a stock at a time, we can apply standard supervised learning methods such as support vector machines (Huang, Nakamori, and Wang 2005) and neural networks (Xu and Cohen 2018) to build the predictive model. Although technically feasible, we argue that such methods could suffer from weak generalization due to the highly stochastic property of stock market. Figure\textsuperscript{1} provides an empirical evidence on the weak generalization, where we split the data into training and validation by time, and train an Attentive LSTM model (Qin et al. 2017) on the historical prices of stocks to predict their movements. From subfigure (a), we can see the training loss gradually decreases with more training epochs, which is as expected. However, the validation loss shown in subfigure (b) does not exhibit a decreasing trend; instead, it only fluctuates around the initialization state without a clear pattern. In other words, the benefits of the model learned on training examples do not translate to improvements on predicting unknown validation examples. Note that we have thoroughly explored the \textit{L\textsuperscript{2}} regularization (results of different lines), which is a common technique to improve model generalization, however, the situation has not improved.

We postulate the reason is that standard classification methods are assumed to learn from stationary inputs, such as pixel values in images and term frequencies in documents. When dealing with stochastic variable such as stock price, the stationary input assumption does not hold and such methods fail to generalize well. Specifically, technical analysis methods for stock prediction typically feed into price-based features, such as the price at a particular timestamp or average price on multiple timestamps (Edwards, Magee, and Bassetti 2007; Nelson, Pereira, and de Oliveira 2017). Since a stock’s price continuously changes with time (during market hours), price-based features are essentially stochastic variable, being fundamentally different from the traditional stationary inputs. To be more specific, the features of a training instance can be seen as a "sample" drawn from the

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\footnotesize{\textsuperscript{2}https://data.worldbank.org/indicator/CM.MKT.LCAP.CD?view=chart

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figures}
\caption{Training process of Attentive LSTM with \textit{L\textsuperscript{2}} regularization coefficient of 0, 0.01, and 0.1.}
\end{figure}
distribution of input variable. Without properly handling the stochasticity of input variables, the method can easily overfit the training data and suffer from weak generalization ability.

In this work, we propose to employ adversarial training to account for the stochastic property of stock market to learn stock movement prediction model. Our primary consideration is that given a training example with fixed input features, we can simulate the stochasticity by adding small perturbations on input features, such that the model’s prediction should not be changed on the perturbed input. To implement this idea, a straightforward solution is to train the model to perform well on both clean examples and perturbed examples, which is the adversarial training method that has been commonly used in computer vision tasks (Kurakin, Goodfellow, and Bengio 2017). However, the problem is that the features to stock prediction models are usually sequential (see Figure 2), such that adding perturbations on the features of all time units can be very time-consuming; moreover, it may cause unintentional interactions among the perturbations of different units which are uncontrollable. To resolve the concern, we instead add perturbations on the high-level prediction features of the model, e.g., the last layer which is directly projected to the final prediction. Since most deep learning methods learn abstract representation in the higher layers, their sizes are usually much smaller than the input size. As such, adding perturbations to high-level features is more efficient, and meanwhile it can also retain the stochasticity.

We implement our adversarial training proposal on an Attentive LSTM model, which is a highly expressive model for sequential data. We add perturbations to the prediction features of the last layer, and dynamically optimize the perturbations to make them change the model’s output as much as possible. We then train the model to make it perform well on both clean features and perturbed features. As such, the adversarial training process can be understood as enforcing a dynamic regularizer, which stabilizes the model training and makes the model perform well under stochasticity.

We investigate the generalization difficulty in stock movement prediction and highlight the necessity of dealing with the stochastic property of input features.

We propose an adversarial training solution to address the stochastic challenge, and implement it on a deep learning model for stock movement prediction.

We conduct extensive experiments on two public benchmarks, demonstrating the usefulness of adversarial training and improvements over several state-of-the-art methods. Codes will be released to facilitate the community.

2 Problem Formulation

First we introduce some notations, including bold capital letters (e.g., \(X\)) and bold lower letters (e.g., \(x\)), which denote matrices and vectors, respectively. Besides, we use normal lower case letters (e.g., \(x\)) and Greek letters (e.g., \(\lambda\)) to represent scalars and hyper-parameters, respectively. All vectors are in column form, if not otherwise specified. The symbols \(\tanh\) and \(\sigma\) stand for the hyperbolic tangent function and sigmoid function, respectively.

Next we present the formulation of the stock movement prediction task, which is to learn a prediction function \(\hat{y} = f(X^s; \Theta)\) mapping a stock \(s\) from the sequential features \((X^s)\) to the label space, where \(\Theta\) are the parameters of \(f\). In other words, the function \(f\) aims to predict the movement of stock \(s\) at the next time-step from the sequential features \(X^s\) in the latest \(T\) time-steps. \(X^s = [x_1^s, \ldots, x_T^s] \in \mathbb{R}^{D \times T}\) is a matrix which represents the sequential input features (e.g., opening and closing prices, as detailed in Table 3) in the lag of past \(T\) time-steps, where \(T\) is a fixed lag size (i.e., length of the sequence) and \(D\) is the dimension of features at a time-step.

Assuming that we have \(S\) stocks, we learn the prediction function by fitting their ground truth labels \(y = [y^1, \ldots, y^S] \in \mathbb{R}^S\), where \(y^s\) is the ground truth label of stock \(s\) in the next time-step. The value of \(y^s\) is \(1\) (-1) if the real movement is up (down). We then formally define the problem as,

Input: A set of training examples \(\{(X^s, y^s)\}\).

Output: A prediction function \(f(X^s; \Theta)\), predicting the movement of stock \(s\) in the following time-step.

In the practical scenario of stock movement prediction, we could typically access a long history of each stock, and construct many training examples for each stock by moving the lag along the history. Nevertheless, we use a simplified formulation without loss of generality by only considering one specific lag (i.e., one training example for each stock) for briefness of presenting the proposed method.

3 Method

In this section, we introduce the proposed solution, named Adversarial Attentive LSTM, including the basic neural network Attentive LSTM and Adversarial Training.

3.1 Attentive LSTM

The Attentive LSTM (ALSTM) mainly contains four components: feature mapping layer, LSTM layer, temporal attention, and prediction layer, as shown in Figure 2.

**Feature mapping layer.** Previous work shows that a deeper input gate would benefit the modeling of temporal structures of LSTM (Graves, Mohamed, and Hinton 2013; Mikolov et al. 2013). Inspired by their success, we employ
a fully connected layer to project the input features into a latent representation. At each time-step, it performs as,

\[ m^*_t = \tanh(W_m x^*_t + b_m), \]

(1)

projecting the input features to a latent space with dimensionality of \( E \), where \( W_m \in \mathbb{R}^{E \times D} \) and \( b_m \in \mathbb{R}^E \) are parameters to be learned. Noting that each entry of the latent representation is a non-linear combination of raw features, the mapping layer shall help to capture the non-linear property of stock features.

**LSTM layer.** Owing to its ability to capture long-term dependency, LSTM has been widely used to process sequential data, such as natural language (Mei, Bansal, and Waller 2016), voice (Graves, Mohamed, and Hinton 2013), and time-series (Qin et al. 2017). The general idea of LSTM is to recurrently project the input sequence into a sequence of hidden representations. At each time-step, the LSTM learns the hidden representation \( h^*_t \) by jointly considering the associate input \( (m^*_t) \) and the previous hidden representation \( (h^*_{t-1}) \) to capture the sequential dependency. Here, we denote it as,

\[ h^*_t = LSTM(m^*_t, h^*_{t-1}), \]

(2)

of which the detailed formulation can be referred to (Hochreiter and Schmidhuber 1997). To capture the sequential dependencies and temporal patterns in the historical features of a stock, we apply an LSTM layer to map the latent representations \([m^*_1, \ldots, m^*_T]\) of a stock into the hidden representations \([h^*_1, \ldots, h^*_T] \in \mathbb{R}^{E \times T}\) with the dimension of \( U \).

**Temporal Attention Layer.** The attention mechanism has been widely used in deep neural networks (Xiao et al. 2017; Song et al. 2018), especially LSTM-based solutions for sequential learning problems, such as machine translation (Cho et al. 2014) and text generation (Xing et al. 2017). The idea of the attention mechanism is to compress the hidden representations at different time-steps into an overall representation of the input sequence with adaptive weights. The attention mechanism aims to model the fact that data at different time-steps could contribute differently to the representation of the whole sequence. For stock representation, status at different time-steps might also contribute differently. For instance, days with maximum and minimum prices in the lag might have higher contributions to the overall representation. As such, we use an attention mechanism to aggregate the hidden representations as,

\[ \alpha^s = \sum_{t=1}^{T} \alpha^*_t h^*_t, \quad \alpha^*_t = \frac{\exp \tilde{\alpha}^*_t}{\sum_{t=1}^{T} \exp \tilde{\alpha}^*_t}; \]

\[ \tilde{\alpha}^*_t = u^*_m \tanh(W_a h^*_t + b_a), \]

(3)

where \( W_a \in \mathbb{R}^{E' \times U} \), \( b_a \) and \( u_a \in \mathbb{R}^{E'} \) are parameters to be learned; and \( \alpha^*_t \) is the aggregated representation that encodes the overall patterns in the sequence.

**Prediction Layer.** Instead of directly making prediction from \( \alpha^s \), we first concatenate \( \alpha^s \) with the last hidden state \( h^*_T \) into the final latent representation of stock \( s \),

\[ e^s = [\alpha^s^T, h^*_T]_T, \]

(4)

where \( e^s \in \mathbb{R}^{2U} \). The intuition behind this is to further emphasize the most recent time-step, which is believed to be informative for the following movement (Fama and French 2012). With \( e^s \), we use a fully connected layer as the predictive function to estimate the classification confidence \( \hat{y}^s = w^*_T e^s + b'_y \). Note that the final prediction is \( \text{sign}(\hat{y}^s) \) (i.e., it is up if \( \hat{y}^s > 0 \), otherwise it is down).

### 3.2 Adversarial Training

As with most classification solutions, the normal way of training the ALSTM is to minimize an objective function \( \Gamma \):

\[ \sum_{s=1}^{S} l(y^s, \hat{y}^s) + \frac{\alpha}{2} ||\Theta||_2^2, \quad l(y^s, \hat{y}^s) = \max(0, 1 - y^s \hat{y}^s), \]

(5)

where \( y^s \) and \( \hat{y}^s \) are the ground-truth and classification confidence of stock \( s \), respectively; \( \Theta \) are model parameters to be learned. The first term is hinge loss (Rosasco et al. 2004), which is widely used for optimizing classification models (more reasons of choosing the hinge loss is further explained in the end of the section). The second term is a regularizer on the trainable parameters to prevent overfitting.

Despite the widely usage of normal training, we argue that it is inappropriate for training stock movement prediction models. This is because normal training assumes that the inputs are stationary, ignoring the stochastic property of these features. Note that the features are calculated from stock price, which is continuously changing with time and affected by stochastic trading behaviours at every specific time (Musgrave 1997). Lacking the ability to capture such stochasticity, normal training might lead to overfitting the data and lacking generalization ability (as shown in Figure 1). To make the model perform well under stochasticity, one intuition is to simulate the stochasticity by adding small perturbations on stationary input features, and enforcing the model to make the same predictions so that it is insensitive to the stochasticity.

**Adversarial training** (Goodfellow, Shlens, and Szegedy 2015; Kurakin, Goodfellow, and Bengio 2017) is an promising option to enhance classification models against perturbations. It is an optimization process that trains a model with both clean examples (i.e., existing examples in the training set) and adversarial examples (Szegedy et al. 2013). The adversarial examples are malicious inputs generated by adding intentional perturbations to clean examples, so that a trained model makes wrong predictions on the adversarial examples. Despite its success in image classification (Kurakin, Goodfellow, and Bengio 2017), it is infeasible to directly apply it on stock prediction, i.e., generating adversarial examples from sequential features. This is because calculating perturbations relies on calculation of the gradients regarding the input, which would be time-consuming (caused by the back-propagation through time of the LSTM layer). Besides, considering the fact that the gradients of the input are dependent across different time-steps, there might be unintentional interactions among the perturbations of different time-steps, which are uncontrollable. To address these problems, we propose to generate adversarial examples from the
final latent representation of the stock instead of its sequential features, as shown in Figure 3, which is more efficient.

Formally, we incorporate an adversarial loss into the training objective function of ALSTM:

\[
\Gamma_{adv} = \sum_{s=1}^{S} l(y_s, \hat{y}_s^s) + \beta \sum_{s=1}^{S} l(y_s^s, \hat{y}_s^{adv}) + \frac{\alpha}{2} \|\Theta\|_F^2, \tag{6}
\]

where \(\hat{y}_s^{adv}\) is the classification confidence of the adversarial example of stock \(s\). \(\beta\) is a hyper-parameter to balance the losses of clean and adversarial examples. By minimizing the objective function, the model is encouraged to correctly classify both clean and adversarial examples. During the minimization, which is typically in an iterative fashion, the adversarial examples are adaptively generated. Specifically, at each iteration, the adversarial examples are generated by adding intentional perturbations to the latent representation of clean examples with the following formulation,

\[
e^{s}_{adv} = e^s + r^s_{adv}, \quad r^s_{adv} = \arg \max_{r^s \in \mathcal{R}} l(y_s^s, \hat{y}_s^{adv}), \tag{7}
\]

where \(e^s\) (introduced in Equation 4) is the final latent representation of stock \(s\). \(r^s_{adv}\) and \(e_{adv}^s\) are the associated perturbation and adversarial example, respectively. \(\epsilon\) is a hyper-parameter to explicitly control the scale of perturbation. Note that the perturbation is optimized to be the direction towards which moving the clean example would cause the largest classification loss, i.e., with the current model parameters, \(y_{adv}^s\), the classification confidence of the adversarial example, leads to large loss. Since it is intractable to directly calculate \(e_{adv}^s\), we employ the fast gradient approximation method (Goodfellow, Shlens, and Szegedy 2015),

\[
r^s_{adv} = \left(\frac{\partial l(y_s^s, \hat{y}_s^{adv})}{\partial e^s}\right)^s, \tag{8}
\]

Intuitively, the calculated perturbation is the gradient of loss function regarding the latent representation \(e^s\) under a \(L_2\)-norm constraint. Note that the gradient denotes the direction where the loss function increase the most at the given point \(e^s\). As such, a model that correctly classifies examples with the adversarial perturbations might also correctly classify examples with stochastic perturbations in the same scale. Therefore, training ALSTM with adversarial learning could enhance its robustness against stochastic perturbations, i.e., enable it to capture the stochastic property of stock features.

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**Figure 3**: Illustration of the Adversarial Attentive LSTM.

**Figure 4**: Illustration of the adversarial training process.

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4.1 Experimental Settings

**Datasets.** To investigate the effectiveness of the proposed method, we conducted experiments on two benchmarks on stock movement prediction, ACL18 (Xu and Cohen 2018) and KDD17 (Zhang, Aggarwal, and Qi 2017), respectively.

- The ACL18 dataset contains end-of-day (EOD) data\(^3\) from Jan-01-2014 to Dec-31-2015 of 88 high-trade-volume-stocks in NASDAQ and New York Stock Exchange. Following (Xu and Cohen 2018), we first align the trading days in the history, i.e., removing weekends and public holidays that lack historical prices. We then move a lag with length of \(T\) along the aligned trading days to construct candidate examples. For a stock, we construct a candidate example at every trading day. Finally, we retain candidate examples of which the movement percent of their adjusted closing prices\(^4\) are \(\geq 0.55\%\) or \(\leq -0.5\%\), and identify them as positive and negative examples, respectively. Besides, we adopt the temporal split

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3 Minimizing the hinge loss of the adversarial example is adjusting \(w_p\) to enlarge \(y^s \hat{y}_adv = y^s (w_p^s e^s + b) = y^s W_p e^s + b = y^s \hat{y}^s\), which would increase the first term \(y^s (w_p^s e^s + b) = y^s \hat{y}^s\). The results in Figure 4 (in Section 4) empirically demonstrate the effect of enforcing margins.

4 The EOD data refers to daily opening, high, low, closing prices and adjusted closing prices of stock.
Table 1: Statistics of the ACL18 dataset.

|          | Training | Validation | Testing |
|----------|----------|------------|---------|
| Duration | Jan-01-2014 | Aug-01-2015 | Oct-01-2015 |
|          | Jul-31-2015 | Sep-30-2015 | Dec-31-2015 |
| #Examples (+) | 10,305 | 1,139 | 1,908 |
| #Examples (-) | 10,010 | 1,416 | 1,812 |

Table 2: Statistics of the KDD17 dataset.

|          | Training | Validation | Testing |
|----------|----------|------------|---------|
| Duration | Jan-01-2007 | Dec-31-2014 | Jan-01-2016 |
|          | Dec-31-2015 | Jan-01-2015 | Dec-31-2016 |
| #Examples (+) | 33,065 | 3,951 | 3,910 |
| #Examples (-) | 31,579 | 4,119 | 3,488 |

Table 3: Features to describe the daily trend of a stock.

| Features          | Calculation |
|-------------------|-------------|
| c_open, c_high, c_low | e.g., \( c_{\text{open}} = \text{open}_t / \text{close}_{t-1} - 1 \) |
| n_close, n_adj_close | e.g., \( n_{\text{close}} = (\text{close}_t / \text{close}_{t-1} - 1 \) |
| 5-day, 10-day, 15-day, 20-day, 25-day, 30-day | e.g., \( 5_{\text{day}} = \sum_{i=5}^{30} \text{adj}_{\text{close}}_{t-i} / 5_{\text{adj}_{\text{close}}_{t}} - 1 \) |

of the identified examples and obtained a training, validation, and testing (detailed statistics in Table 1). Note that we ignore the textual contents in the original dataset since we focus on the modeling of stock prices.

- The KDD17 dataset includes EOD data with longer history ranging from Jan-01-2007 to Dec-31-2015 of 50 stocks in U.S. markets. As the dataset is originally collected for predicting stock prices rather than movements, we follow the same approach as ACL18 to identify positive and negative examples. We then temporally split the examples into training, validation and testing, of which the detailed statistics are summarized in Table 2.

Features. Instead of using the raw EOD data, we define 11 temporal features \( (x_t^s) \) to describe the trend of a stock \( s \) at trading day \( t \). Table 3 elaborates the features associated with calculation. Our intuition of defining these features are to: 1) normalize the prices of different stocks, which range from 1.96 to 272,885.0 dollars; 2) explicitly capture the interaction of different prices (e.g., opening and closing).

Baselines. We compare the proposed Adv-ALSTM with the following methods:

- RAND is a naive method that randomly predicts up or down for each example.
- LSTM is a neural network with an LSTM layer and a prediction layer [Nelson, Pereira, and de Oliveira 2017]. We tune three hyper-parameters, number of hidden units (\( U \)), lag size (\( T \)), and weight of regularization term (\( \lambda \)).
- ALSTM is the Attentive LSTM, i.e., LSTM with temporal attention [Qin et al. 2017], optimized with normal training. Similar as LSTM, we also tune three hyper-parameters, \( U \), \( T \), and \( \lambda \).
- StockNet uses a Variational Autoencoder (VAE) to encode the stock input so as to capture the stochasticity, and a temporal attention to model the importance of different time-steps [Xu and Cohen 2018]. Here we take our temporal features in Table 3 as inputs and tune its hidden size, dropout ratio, and auxiliary rate (\( \alpha \)).

Note that we ignore the potential baselines based on conventional time-series models such as ARIMA since they have been reported to be less effective than LSTM and StockNet [Zhang, Aggarwal, and Qi 2017; Xu and Cohen 2018].

Evaluation Metrics. We follow [Xu and Cohen 2018] and evaluate the prediction performance with two metrics, Accuracy (Acc) and Matthews Correlation Coefficient (MCC) of which the ranges are in \([0, 100] \) and \([-1, 1] \). Note that better performance is evidenced by higher value of the metrics.

Parameter Settings. We implement the Adv-ALSTM with Tensorflow and optimize it using the mini-batch Adam [Kingma and Ba 2015] with a batch size of 1,024 and an initial learning rate of 0.01. We search the optimal hyper-parameters of Adv-ALSTM on the validation set. For \( U \), \( T \), and \( \lambda \), Adv-ALSTM inherits the optimal settings from ALSTM, which are selected via grid-search within the ranges of \([4, 8, 16, 32] \), \([2, 3, 4, 5, 10, 15] \), and \([0.001, 0.01, 0.1, 1] \), respectively. We further tune \( \beta \) and \( \epsilon \) within \([0.001, 0.005, 0.01, 0.05, 0.1, 0.5, 1] \) and \([0.001, 0.005, 0.01, 0.05, 0.1] \), respectively. We report the testing performance when Adv-ALSTM performs best on the validation set with \( U = 4, S = 5, \alpha = 1.0, \beta = 0.01, \epsilon = 0.05 \) and \( U = 16, S = 15, \alpha = 0.001, \beta = 0.05, \epsilon = 0.001 \) on the ACL18 and KDD17 datasets, respectively. Note that the implementation and model parameters of Adv-ALSTM would be publicly accessible through [https://anonymous.com](https://anonymous.com).

4.2 Experimental Results

Performance Comparison. We first investigate how Adv-ALSTM performs as compared to state-of-the-art stock movement prediction methods. Tables 4 and 5 show the prediction performance of compared methods on the two datasets regarding Acc and MCC, respectively. Note that the performance of RAND and StockNet in Table 4 are directly copied from [Xu and Cohen 2018] (StockNet is denoted as TECHNICAL ANALYST), of which our implementation achieves slightly worse performance. The remaining results are the mean performance of five repeated runs. From the results, we have the following observations:

- Adv-ALSTM achieves the best results in all the cases. Compared to the baselines, Adv-ALSTM exhibits an improvement of 4.02% and 42.19% (2.14% and 56.12%) on the ACL18 (KDD17) dataset regarding Acc and MCC, respectively. This justifies the effectiveness of adversarial training, which might be due to enhancing the model generalization via adaptively simulating perturbations during the training.

- Specifically, compared to StockNet, which captures stochasticity of stock inputs with VAE, Adv-ALSTM achieves significant improvements. We postulate the reason is that StockNet cannot explicitly model the scale and direction of stochastic perturbation since it relies on Monte Carlo sampling during the training process.
Table 4: Performance of compared methods on the ACL18 dataset. RI denotes the relative improvement of Adv-ALSTM compared to the associated baseline.

| Methods   | Acc      | RI       | MCC     | RI       |
|-----------|----------|----------|---------|----------|
| RAND      | 50.89±1e-1 | 12.40%   | -0.0023±— | —        |
| LSTM      | 53.18±5e-1 | 7.56%    | 0.0067±5e-3 | 120.03% |
| ALSTM     | 54.90±7e-1 | 4.02%    | 0.1043±7e-3 | 42.19%  |
| StockNet  | 54.96±—    | 4.08%    | 0.0165±—   | 79.79%  |
| Adv-ALSTM | 57.20±—    | —        | 0.1453±—  | 1276.32%|

Table 5: Performance of compared methods on the KDD17 dataset. RI denotes the relative improvement of Adv-ALSTM compared to the associated baseline.

| Methods | Acc | RI       | MCC     | RI       |
|---------|-----|----------|---------|----------|
| RAND    | 50.19±4e-1 | 5.70%    | 0.0038±8e-3 | 1276.32%|
| LSTM    | 51.62±4e-1 | 2.77%    | 0.0183±6e-3 | 185.79% |
| ALSTM   | 51.94±7e-1 | 2.14%    | 0.0261±1e-2 | 100.38% |
| StockNet| 51.93±4e-1 | 2.14%    | 0.0335±5e-3 | 56.12%  |
| Adv-ALSTM | 53.05±—    | —        | 0.0523±—   | —        |

Table 6: Performance of Rand-ALSTM on the two datasets.

| Datasets | Acc         | MCC         |
|----------|-------------|-------------|
| ACL18    | 55.08±2e-1 | 0.1101±4e-2 |
| KDD17    | 52.43±5e-1 | 0.0403±8e-3 |

- Among the baselines, ALSTM outperforms LSTM by 1.93% and 48.69% on average w.r.t. Acc and MCC, which demonstrates the impact of attention mechanism (Qin et al. 2017). Besides, Rand performs worse than all the machine learning-based methods as expected, which justifies that historical patterns help in stock prediction task.

Stochastic Perturbation VS Adversarial Perturbation. We further investigate the effectiveness of adversarial training via comparing adversarial perturbations and random ones. Rand-ALSTM is a variance of Adv-ALSTM, which adds random perturbation to clean examples. We tune its hyper-parameters in the same way as that of Adv-ALSTM. Table 6 shows the performance of Rand-ALSTM on the two datasets. By cross comparing it with Tables 4 and 5, we observe that: 1) Compared to Rand-ALSTM, Adv-ALSTM achieves significant improvements. For instance, its performance w.r.t. Acc on ACL18 is 3.95% better than that of Rand-ALSTM. It demonstrates that adversarial perturbations are helpful for stock prediction, similar to that reported in the original image classification tasks (Goodfellow, Shlens, and Szegedy 2015). 2) Rand-ALSTM outperforms ALSTM, which is purely trained with clean examples, with an average improvement of 0.64% w.r.t. Acc on the two datasets. This highlights the necessity of dealing with stochastic property of stock features.

Impacts of Adversarial Training. We now investigate the impacts of adversarial training to answer:

- Whether the adversarial training enforces the margin between clean examples and the decision boundary.
- Whether the adversarial training enhances the robustness of the model against adversarial examples.

Note that we only show the results on the ACL18 dataset because of space limitation, as the results on KDD17 admit the same observations.

Enforcing margin. To answer the first question, we compare the margin between the clean examples and the decision boundary of ALSTM and Adv-ALSTM. Recall that Adv-ALSTM is initialized with parameters of ALSTM and further trained with adversarial learning. As such, their difference reflects the impact of adversarial learning. Specifically, we calculate the classification confidence of each clean examples (larger value denotes larger margin to the decision boundary) in the validation and testing sets.

Figures 5(a) and 5(b) illustrate the distributions of the classification confidence assigned by ALSTM and Adv-ALSTM for clean examples in validation and testing.

Figure 5: Distributions of classification confidences assigned by ALSTM and Adv-ALSTM for clean examples in validation and testing.

Figure 6: Robustness against adversarial example of ALSTM and Adv-ALSTM. The plotted numbers are the relative performance decrease (w.r.t. Acc and MCC) of trained models on adversarial examples compared to clean ones.

Figure 6: Robustness against adversarial example of ALSTM and Adv-ALSTM. As can be seen, the confidences of Adv-ALSTM distribute in a range ([−0.6, 0.6] roughly), which is about 1.5 times larger than that of ALSTM ([−0.2, 0.3]). This verifies that the adversarial training pushes the decision boundary far from clean examples, which is believed to help enhance the robustness and generalization ability of the model.

Robustness against adversarial examples. We then investigate the second question via comparing the performance of ALSTM and Adv-ALSTM on the clean and associated adversarial examples, which are generated with Equation 7 under the converged parameters of each method. Specifically, for each method, we separately calculate its performance on the clean and adversarial examples (i.e., we have a pair of performance on the training, validation, and testing separately). For each pair of performance, we then calculate the relative decrease of performance on adversarial examples regarding the one on clean examples (larger value indicates more vulnerable to adversarial perturbations).
Figures 6(a) and 6(b) illustrate the relative performance decrease of ALSTM and Adv-ALSTM w.r.t. Acc and MCC, respectively. From the results, we observe that the average relative performance decreases of ALSTM are 4.31 and 6.34 times larger, as compared to Adv-ALSTM, regarding Acc and MCC, respectively. This justifies the potential of enhancing model robustness with adversarial training. Moreover, while much smaller than ALSTM, Adv-ALSTM still suffers a small performance decrease (e.g., the average relative decrease is 0.5% regarding Acc). This indicates that adversarial training cannot resist all adversarial examples, which is also reported in the previous work of (Goodfellow, Shlens, and Szegedy 2015; Kurakin, Goodfellow, and Bengio 2017), and needs further exploration in future.

5 Related Work

Stock Movement Prediction. Recent works on stock movement prediction, mainly fall under two categories, technical analysis and fundamental analysis: The technical analysis, which mainly analyzes historical prices, i.e., takes historical prices of a stock as features to forecast its movement. With the development of deep learning, especially deep neural networks, most of recent researches mine stock movements with deep models (Lin, Guo, and Aberer 2017; Nelson, Pereira, and de Oliveira 2017; Hu et al. 2017). Among them, recurrent neural networks like LSTM have become key components to capture the temporal patterns lying in stock prices (Nelson, Pereira, and de Oliveira 2017; Lin, Guo, and Aberer 2017). Besides, other advanced neural models, such as convolution neural networks (Hu et al. 2017) and deep Boltzmann machine (Chong, Han, and Park 2017), are also evidenced to be beneficial for capturing the non-linearity of stock prices.

Besides historical prices of stocks, the fundamental analysis also examines related economic, financial, and other qualitative and quantitative factors (Hu et al. 2018; Zhang et al. 2018; Li et al. 2018; Xu and Cohen 2018). For instance, Xu and Cohen (2018) incorporate signals from social media, which reflects opinions from general users, to enhance stock movement prediction. Specifically, they employ a Variational Autoencoder to learn a stock representation from both its historical prices and the tweets mentioning it. Moreover, Zhang et al. (2018) further consider news events related to a stock or the associated company via a coupled matrix and tensor factorization framework. Although these fundamental analysis studies show that examining more factors enhances the prediction performance, incorporating more factors inevitably increases the complexity of the prediction models and leads to difficulty of model optimization.

As assuming stock price as stationary input, existing methods, except StockNet (Xu and Cohen 2018), lack the ability to deal with its stochastic property (perturbation). StockNet tackles this problem relying on a VAE that takes the inputs as stochastic variables and encodes them into a latent representation which follows standard Gaussian distribution. The intuition behind StockNet is enforcing samples (examples) from the latent distribution, which can be seen as simulation of stochastic perturbations, to be decoded with the same label (prediction) as the input example. Since relying on Monte Carlo approximation and typically accounting for only one sample during the optimization, the effect of StockNet is largely equal to generating one example with stochastic perturbation from the input. However, randomly sampling from the latent distribution leads to that StockNet is uncontrollable to the scale and direction of perturbation, which is the key difference as compared to our method. Besides, it should be noted that the proposed method can be easily generalized to the fundamental analysis, considering that most methods of fundamental analysis also learn an embedding for each example, to which perturbations can be added to generate adversarial examples.

Adversarial Learning. Adversarial learning has been intensively studied by training a classification model to defend adversarial examples, which are intentionally generated to perturb the model. Existing works of adversarial learning mainly concentrate on computer vision tasks like image classification (Goodfellow, Shlens, and Szegedy 2015; Miyato, Dai, and Goodfellow 2017; Kurakin, Goodfellow, and Bengio 2017). Owing to the property that image features are typically continued real values, adversarial examples are directly generated in the feature space. Recently, several works extend the adversarial learning to tasks with discrete inputs such as text classification (a sequence of words) (Miyato, Dai, and Goodfellow 2017), recommendation (user and item IDs) (He et al. 2018), and graph node classification (graph topology) (Dai et al. 2018). Rather than in the feature space, these works generate adversarial examples from embedding of inputs such as word, user (item), and node embeddings. Although this work is inspired by these adversarial learning research efforts, it targets a distinct task—stock movement prediction, of which the data are time series with stochastic property. To the best of our knowledge, this work is the first one to explore the potential of adversarial training in time-series analytics.

6 Conclusion

In this paper, we show that neural network solutions for stock movement prediction could suffer from weak generalization ability since they lack the ability to deal with the stochasticity of stock features. To solve this problem, we propose an Adversarial Attentive LSTM solution, which leverages adversarial training to simulate the stochasticity and to enhance the generalization ability of the model. We conduct extensive experiments on two benchmark datasets and justify the effectiveness of the proposed solution, signifying the importance of accounting for the stochasticity of stock prices in stock movement prediction.

In future, we plan to explore the following directions: 1) we are interested in extending the proposed Adv-ALSTM to solve other stock prediction tasks such as the stock prices (Zhang, Aggarwal, and Qi 2017). 2) We plan to investigate whether adversarial training is effective for training stock movement solutions with other neural network structures such as the convolutional neural networks (Lin, Guo, and Aberer 2017). 3) We will explore the effect of adversarial training over methods under fundamental analysis.
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