Predicting the daily return direction of the stock market using hybrid machine learning algorithms

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Abstract

Big data analytic techniques associated with machine learning algorithms are playing an increasingly important role in various application fields, including stock market investment. However, few studies have focused on forecasting daily stock market returns, especially when using powerful machine learning techniques, such as deep neural networks (DNNs), to perform the analyses. DNNs employ various deep learning algorithms based on the combination of network structure, activation function, and model parameters, with their performance depending on the format of the data representation. This paper presents a comprehensive big data analytics process to predict the daily return direction of the SPDR S&P 500 ETF (ticker symbol: SPY) based on 60 financial and economic features. DNNs and traditional artificial neural networks (ANNs) are then deployed over the entire preprocessed but untransformed dataset, along with two datasets transformed via principal component analysis (PCA), to predict the daily direction of future stock market index returns. While controlling for overfitting, a pattern for the classification accuracy of the DNNs is detected and demonstrated as the number of the hidden layers increases gradually from 12 to 1000. Moreover, a set of hypothesis testing procedures are implemented on the classification, and the simulation results show that the DNNs using two PCA-represented datasets give significantly higher classification accuracy than those using the entire untransformed dataset, as well as several other hybrid machine learning algorithms. In addition, the trading strategies guided by the DNN classification process based on PCA-represented data perform slightly better than the others tested, including in a comparison against two standard benchmarks.

Keywords: Daily stock return forecasting, Return direction classification, Data representation, Hybrid machine learning algorithms, Deep neural networks (DNNs), Trading strategies

Introduction

Big data analytic techniques developed with machine learning algorithms are gaining more attention in various application fields, including stock market investment. This is mainly because machine learning algorithms do not require any assumptions about the data and often achieve higher accuracy than econometric and statistical models; for example, artificial neural networks (ANNs), fuzzy systems, and genetic algorithms are driven by multivariate data with no required assumptions. Many of these methodologies have been applied to forecast and analyze financial variables, for instance, see Vellido, Lisboa, &

Meehan (1999); Kim & Han (2000); Cao & Tay (2001); Thawornwong, Dagli, & Enke (2001); Bogullu, Enke, & Dagli (2002); Hansen & Nelson (2002); Wang (2002); Chen, Leung, & Daouk (2003); Zhang (2003); Chun & Kim (2004); Shen & Loh (2004); Thaworn-wong & Enke (2004); Armano, Marchesi, & Murru (2005); Enke & Thawornwong (2005); Ture & Kurt (2006); Amornwattana et al. (2007); Enke & Mehdiyev (2013); Zhong & Enke (2017a, 2017b); Huang & Kou (2014); Huang, Kou, & Peng (2017); and Nayak & Misra (2018). A comprehensive review of these studies was conducted by Atsalakis & Valavanis (2009) and Vanstone & Finnie (2009). With nonlinear, data-driven, and easy-to-generalize characteristics, multivariate analysis with ANNs has become a dominant and popular ana-lysis tool in finance and economics. Refenes, Burgess, & Bentz (1997) and Zhang, Patuwo, & Hu (1998) review the use of using ANNs as a forecasting method in different areas of fi-nance and investing, including financial engineering.

Recently, deep learning has emerged as a powerful machine learning technique owing to its far-reaching implications for artificial intelligence, although deep learning methods are not currently considered as an all-encompassing solution for the effective application of artificial intelligence. ANNs using different deep learning algorithms are categorized as deep neural networks (DNNs), which have been applied to many important fields, such as automatic speech recognition, image recognition, natural language processing, drug discovery and toxicology, customer relationship management, recommendation systems, and bioinformatics where they have often been shown to produce improved results for dif-ferent tasks.

Moreover, it is critical for neural networks with different topologies to achieve accurate results with a deliberate selection of input variables (Lam, 2004; Hussain et al., 2007). The most influential and representative inputs can be chosen using mature dimensionality re-duction technologies, such as principal component analysis (PCA), and its variants fuzzy robust principal component analysis (FRPCA) and kernel-based principal component ana-lysis (KPCA), among others. PCA is a classical and well-known statistical linear method for extracting the most influential features from a high-dimensional data space. van der Maaten et al. (2009) compare PCA with 12 front-ranked nonlinear dimensionality reduc-tion techniques, such as multidimensional scaling, Isomap, maximum variance unfolding, KPCA, diffusion maps, multilayer autoencoders, locally linear embedding, Laplacian eigen-maps, Hessian LLE, local tangent space analysis, locally linear coordination, and manifold charting, by applying each on self-created and natural tasks. The results show that al-though nonlinear techniques perform well on selected artificial data, none of them outper-forms the traditional PCA using real-world data. In addition, Sorzano, Vargas, & Pascual-Montano (2014) state that among the available dimensionality reduction tech-niques, PCA and its versions, such as the standard PCA, robust PCA, sparse PCA, and KPCA, are still preferred for their simplicity and intuitiveness.

Few studies have focused on forecasting daily stock market returns using hybrid machine learning algorithms. Zhong & Enke (2017a) present a study of dimensionality reduction with an application to predict the daily return direction of the SPDR S&P 500 ETF (ticker symbol: SPY) using ANN classifiers. They compare various ANN models and find that among the PCA and its two popular variants, FRPCA and KPCA, PCA-based ANN classi-fiers are shown to be the best predictor of the ETF daily return direction over various data-sets transformed using PCA (Zhong & Enke, 2017a). Also, Zhong & Enke (2017b) perform a comprehensive data mining procedure, including both cluster and classification mining,

to forecast the ETF daily return direction. They show that PCA-based ANN classifiers lead to significantly higher accuracy than three different PCA-based logistic regression models, including those that have successfully used fuzzy c-means clustering. Chong, Han, & Park (2017) recently examine the advantages and drawbacks of using deep learning algorithms for stock analysis and prediction, but their study focuses on intraday stock return forecasting.

In this study, the daily return direction of the SPDR S&P 500 ETF is forecasted using a deliberately designed classification mining procedure based on hybrid machine learning algorithms. This process begins by preprocessing the raw data to deal with missing values, outliers, and mismatched samples. The ANNs and DNNs, each acting as classifiers, are then used with both the entire untransformed dataset and the PCA-represented datasets to forecast the direction of future daily market returns. The remainder of this paper discusses the details of the study and is organized as follows. The data description and preprocessing are introduced next, including the transformation of the entire data set via PCA. The architectures, network topology, and learning algorithms of the newly developed DNNs, along with the previously successful benchmark ANNs, both of which are used for return direction classification, are then discussed. The forecasting procedure of three different datasets with the DNN classifiers are then described, together with the classification results and the pattern of the classification accuracy relevant to the number of hidden layers. A standard benchmark is also compared with the PCA-based ANN classifiers results. The simulation results from trading strategies based on the DNN classifiers over the three datasets are compared to each other, and the results of the ANN-based trading strategies as compared with two benchmarks are then discussed. Finally, concluding remarks and proposed future work are provided.

Data description and preprocessing

Data description

The dataset utilized in this study includes the daily direction (up or down) of the closing price of the SPDR S&P 500 ETF (ticker symbol: SPY) as the output, along with 60 financial and economic factors as input features. This daily data is collected from 2518 trading days between June 1, 2003 and May 31, 2013. The 60 potential features can be divided into 10 groups, including the SPY return for the current day and the three previous days, the relative difference in percentage of the SPY return, the exponential moving averages of the SPY return, Treasury bill (T-bill) rates, certificate of deposit rates, financial and economic indicators, term and default spreads, exchange rates between the USD and four other currencies, the return of seven major world indices (other than the S&P 500), the SPY trading volume, and the return of eight large capitalization companies within the S&P 500 (which is a market cap weighted index and driven by the larger capitalization companies within the index). These features, which are a mixture of those identified by various researchers (Cao & Tay, 2001; Thawornwong & Enke, 2004; Armano, Marchesi, & Murru, 2005; Enke & Thawornwong, 2005; Niaki & Hoseinzade, 2013; and Zhong & Enke, 2017a, 2017b), are included as long as their values are released without a gap of more than five continuous trading days during the study period. The details of these 60 financial and economic factors, including their descriptions, sources, and calculation formulas, are given in Table 10 of the Appendix.

Data preprocessing

Data normalization

Given that the data used in this study cover 60 factors over 2518 trading days, there invariably exist missing values, mismatching samples, and outliers. Yet, the data quality is an important factor that can make a difference in the prediction accuracy, and therefore, preprocessing the raw data is necessary. Using the 2518 trading days during the 10-year period, the collected samples from other days are initially deleted. If there are n values for any variable or column that are continuously missing, the average of the n existing values on both sides of the missing values are used to fill in the n missing values. A simple but classical statistical principle is employed to detect the possible outliers (Navidi, 2011). The possible outliers are then adjusted using a similar method to the one used by Cao & Tay (2001). Specifically, for each of the 60 factors or columns in the data, any value beyond the interval $(Q_1 - 1.5 * IQR, Q_3 + 1.5 * IQR)$ is regarded as a possible outlier, with the factor value replaced by the closer boundary of the interval. Here, Q_1 and Q_3 are the first and third quartiles, respectively, of all the values in that column, and $IQR = Q_3 - Q_1$ is the interquartile of those values. The symmetry of all adjusted and cleaned columns can be checked using histograms or statistical tests. For example, Figure 1 includes the histograms of factor SPY_t (i.e., the SPY current daily return), before and after data preprocessing (Zhong & Enke, 2017a). It can be observed that the outliers are removed, and the symmetry is achieved after adjustments.

In this study, the ANNs and DNNs for pattern recognition are used as the classifiers. At the start of the classification mining procedure, the cleaned data are sequentially partitioned into three parts: training data (the first 70% of the data), validation data (the last 15% of the first 85% of the data), and the testing data (the last 15% of the data).

Data transformation using PCA

As one of the earliest multivariate techniques, PCA aims to construct a low-dimensional representation of the data while maintaining the maximal variance and covariance structure of the data (Jolliffe, 1986). To achieve this goal, a linear mapping W that can maximize $W^T var(X)W$, where $var(X)$ is the variance-covariance matrix of the data X, needs to be created. Given that W is formed by the principal eigenvectors of $var(X)$, PCA turns out to be an eigenproblem $var(X)W = \lambda W$, where λ represents the eigenvalues of $var(X)$. It is also
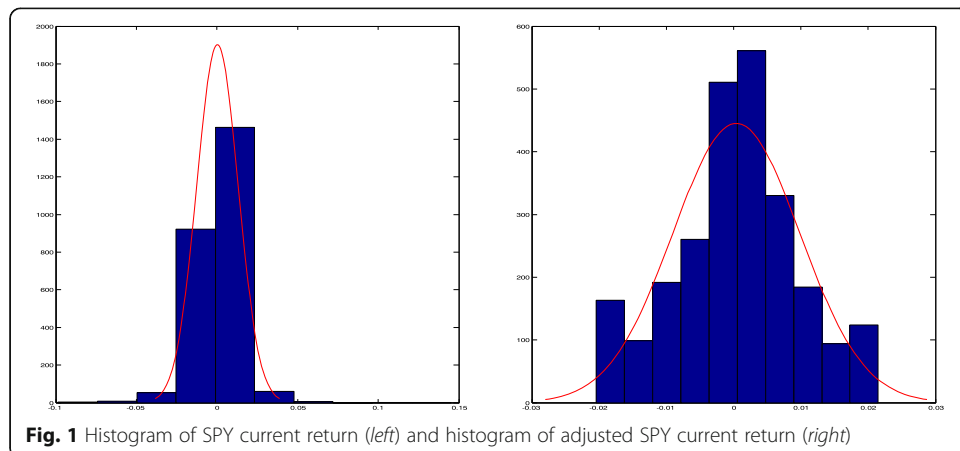

Fig. 1 Histogram of SPY current return (*left*) and histogram of adjusted SPY current return (*right*)

known that working on the raw data X instead of the standardized data with the PCA tends to emphasize variables that have higher variances more than variables that have very low variances, especially if the units where the variables are measured are inconsistent. In this study, not all variables are measured at the same units. Thus, here, PCA is actually applied to the standardized version of the cleaned data X. The specific procedure is given below.

First, the linear mapping W^* is searched such that

$$corr(X)W^* = \lambda^* W^*, \tag{1}$$

and $corr(X)$ is the correlation matrix of the data X. Assume that the data X has the format $X = (X_1\ X_2 \cdots X_M)$; then $corr(X) = \rho$ is a $M \times M$ matrix, where M is the dimensionality of the data, and the ij^{th} element of the correlation matrix is

$$corr(X_i, X_j) = \rho_{ij} = \frac{\sigma_{ij}}{\sigma_i \sigma_j},$$

where.

$$\sigma_{ij} = cov(X_i, X_j), \sigma_i = \sqrt{var(X_i)}, \sigma_j = \sqrt{var(X_j)}, \text{and } i, j = 1, 2, ..., M. \tag{2}$$

Let $\lambda^* = \{\lambda_i^*\}_{i=1}^M$ denote the eigenvalues of the correlation matrix $corr(X)$ such that $\lambda_1^* \geq \lambda_2^* \geq \cdots \geq \lambda_M^*$ and the vectors $e_i^T = (e_{i1}\ e_{i2} \cdots e_{iM})$ denote the eigenvectors of $corr(X)$ corresponding to the eigenvalues λ_i^*, $i = 1, 2, ..., M$. The elements of these eigenvectors can be proven to be the coefficients of the principal components.

Secondly, the principal components of the standardized data are presented as

$$Z = (Z_1\ Z_2 \cdots Z_M),$$

where.

$$Z_w^T = (Z_{1w} Z_{2w} \cdots Z_{Nw}), Z_{vw} = \frac{X_{vw} - \mu_w}{\sigma_w}, v = 1, 2, ..., N, \text{and } w = 1, 2, ..., M \tag{3}$$

can be written as.

$$Y_i = \sum_{j=1}^M e_{ij} Z_j, i = 1, 2, ..., M \tag{4}$$

Using the spectral decomposition theorem,

$$\rho = \sum_{i=1}^M \lambda_i^* e_i e_i^T \tag{5}$$

and the fact that $e_i^T e_i = \sum_{j=1}^M e_{ij}^2 = 1$ and the different eigenvectors are perpendicular to each other such that $e_i^T e_j = 0$, we can prove that

$$var(Y_i) = \sum_{k=1}^M \sum_{l=1}^M e_{ik} corr(X_k, X_l) e_{il} = e_i^T \rho e_i = \lambda_i^* \tag{6}$$

and

$$cov(Y_i, Y_j) = \sum_{k=1}^M \sum_{l=1}^M e_{ik} corr(X_k, X_l) e_{jl} = e_i^T \rho e_j = 0. \tag{7}$$

That is, the variance of the ith (largest) principal component is equal to the ith largest eigenvalue, and the principal components are mutually uncorrelated.

In summary, the principal components can be written as the linear combinations of all the factors with the corresponding coefficients equaling the elements of the eigenvectors. Different amounts of principal components can explain different proportions of the variance-covariance structure of the data. The eigenvalues can be used to rank the eigenvectors based on how much of the data variation is captured by each principal component.

Theoretically, the information loss due to the dimensionality reduction of the data space from M to k is insignificant if the proportion of the variation explained by the first k principal components is large enough. In practice, the chosen principle components must be those that best explain the data while simplifying the data structure as much as possible.

Neural networks for pattern recognition

Recognized as one of the most important machine learning technologies, ANNs can be viewed as a cascading model of cell types emulating the human brain by carefully defining and designing the network architecture, including the number of network layers, the types of connections among the network layers, the numbers of neurons in each layer, the learning algorithm, the learning rate, the weights among neurons, and the various neuron activation functions. All these parameters are typically determined empirically during the learning or training phase of the neural network modeling. Thus, it is usually not easy to interpret the symbolic meaning of the trained results. However, the neural networks have high tolerance for noisy data and perform very well in recognizing the different patterns of new data during the testing stage. Also, some efficient algorithms have recently been developed to extract the classification rules from the trained neural networks. The backpropagation algorithm is well accepted as the most popular neural network learning algorithm, which is often carried out using a multilayer feed-forward neural network.

Multilayer feed-forward neural networks

Among the various types of neural networks that have been developed, the multilayer feed-forward network is most commonly used for pattern recognition, including classification, in data mining. Such a feed-forward neural network is illustrated in Fig. 2.

In Fig. 2, X_i, $i = 1, 2, \ldots, I$, denotes the ith component (neuron) of the input vector (layer) including I components (neurons); H_j, $j = 1, 2, \ldots, J$, denotes the jth neuron in the hidden layer with J neurons; and O_k, $k = 1, 2, \ldots, K$, denotes the kth neuron in the output layer. The connections between each neuron of two adjacent layers exist with empirically adjusted weights. For example, w_{ij} denotes the weight between the ith neuron in the input layer and the jth neuron in the hidden layer. Given enough hidden neurons, multilayer feed-forward neural networks of linear threshold functions can closely approximate any function. The number of hidden layers is arbitrary, depending on the complexity of the neural networks. A boundary of 10 is usually used to differentiate shallow neural networks from DNNs. That is, if the feed-forward neural networks involve more than 10 hidden layers, they are considered DNNS; otherwise, shallow neural networks are referred to. More details on DNNs are given in the next section.

Fig. 2 Topology of a multilayer feed-forward neural network used for classification
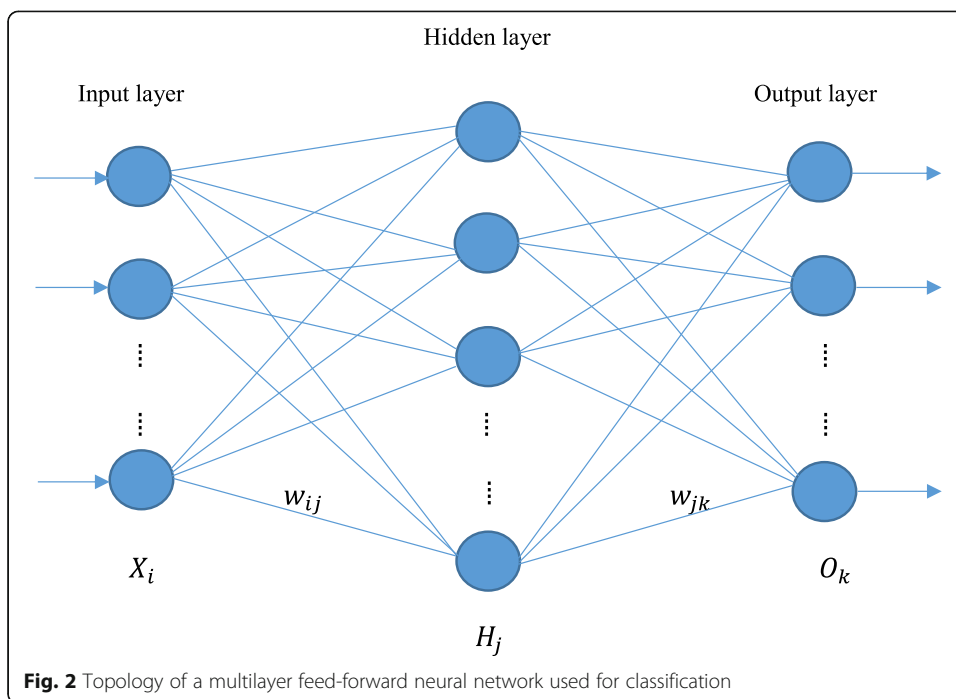
Traditional feed-forward ANNs often utilize the backpropagation learning algorithm (*Rumelhart*, et al., 1986) based on an iterative process where the connection weights between the layers are adjusted repeatedly in a backwards direction, from the output layer, through the hidden layers, and then to the first hidden layer, such that the difference between the predicted class and the true class measured by the mean squared error (MSE) can be minimized during the procedure. Although other sophisticated learning algorithms have been developed over the years for specific applications, the traditional backpropagation learning is still often used to train newly developed DNNs.

DNNs for classification

More recently, deep learning, also known as deep structured learning, hierarchical learning, or deep machine learning, has emerged as a promising branch of machine learning based on a set of algorithms that attempt to model high-level abstractions in data by using a deep graph with multiple processing layers composed of numerous linear and nonlinear transformations. This concept was introduced to the machine learning community by Dechter (1986), and later to those working with ANNs (Aizenberg et al., 2000). Researchers in this area attempt to develop better representations and models for learning these representations from large-scale unlabeled data, compared to shallow learning, where the number of hidden layers is usually not greater than 10.

Since the first functional DNNs using a learning algorithm called the group method of data handling are published by Ivakhnenko (1973) and his research group, a large number of DNN architectures, such as pattern recognition networks, convolutional neural networks, recurrent neural networks, and long short-term memory, have been explored. Because more hidden layers and neurons are involved in DNNs, the computational power of DNNs is expected to be higher than traditional ANNs. However, DNNs, like ANNs, suffer

from overfitting, which results from the estimation of a large number of parameters used to define the connections among hidden layers and neurons involved in DNNs, thereby reducing the model's generalization ability.

Forecasting daily return direction of the SPDR S&P 500 ETF

This study focuses on predicting the daily return direction of the SPDR S&P 500 ETF (ticker symbol: SPY) for the next day. The direction forecast can be either up or down. A direction forecast (up or down) is used instead of a level forecast since this study's objective is to not only develop a forecasting model with high classification accuracy, but also develop a model that can be used successfully in a practical trading environment. Previous studies (e.g., Thawornwong & Enke, 2004) have shown that when developing forecasting/trading systems, direction forecasts (up or down) perform better in a trading environment/simulation than level forecasts (predicting the exact value of the stock or index one period forward). While level forecasts can result in models with higher reported training/testing prediction accuracy (greater than 90% in some instances), often these models are over-fitted to the data to achieve these results. Consequently, such models are more likely to suffer in a trading environment/simulation. On the other hand, since a small miss is still a miss (e.g., predicting up but being slightly down), successful direction forecasts are more likely to have a prediction accuracy closer to 60%; yet, these models still perform better at these accuracy levels when simulating real-world trading since the results from these models are more likely to be on the right side of the trade. Therefore, the following modeling focuses on making an accurate and ideally profitable direction forecast.

For the model testing, three different datasets are employed, with or without the use of a PCA transformation. Trading simulations of return versus risk for the best models are discussed later.

Use of ANN and DNN classifiers

The architecture of the DNNs considered in this study is designed as a pattern recognition network with a large number of hidden layers (i.e., more than 10 hidden layers); the architecture of the ANNs is also designed as a pattern recognition network with the number of hidden layers set to 10. The pattern recognition network used is typical of the type of multilayer feed-forward neural networks that are specifically designed for classification problems (Chiang et al., 2016; Kim & Enke, 2016; Zhong & Enke, 2017a, b). The MATLAB R2017b software is used for the modeling and testing, and the MSE and confusion matrix are used for the analysis and comparison, specifically for the evaluation of the performance of the ANN and DNN classifiers. The confusion matrix consists of four correctness percentages for the training, validation, testing, and total dataset that are provided as inputs to the classifiers. The percent of correctness indicates the fraction of samples that are correctly classified. A value of 0 means no correct classification, whereas a value of 100 indicates maximum correct classifications. Specifically, the Neural Network Toolbox in MATLAB R2017b functions in the following way. The training data are input to train the model, while the validation data are input to control the classifiers' overfitting problem almost simultaneously. That is, as each classifier is trained using the training data, the MSE obtained from classifying the validation data with the trained model decreases and continues to do so for a certain amount of time; the MSE of the validation starts to increase

when the model suffers from overfitting, resulting in the need for the training phase to be terminated. Thus, the model can be best trained in the sense that the validation phase achieves its lowest MSE with the trained model. After the model is trained and selected, all training data, validation data, and testing data (untouched) are provided as inputs and classified by the trained model separately. The percentage of correctly predicted or classified daily directions corresponding to each category can be obtained and recorded.

Table 1 shows the classification results of the traditional benchmark ANN using 12 transformed datasets. It shows that the benchmark ANN classifier achieves the highest accuracy in the testing phase over the PCA-represented dataset with 31 principal components; the PCA-represented dataset with 60 principal components gives the second best results.

Three datasets are considered for the DNN analysis. The first dataset includes the entire preprocessed but untransformed data, including 60 factors. The second and third datasets are transformed datasets using PCA, with 60 and 31 principal components, respectively (i.e., data with PCA equal to 60 and 31 are used since the benchmark ANN classifier achieves the highest accuracy levels in the testing phase when using the PCA-represented datasets with 31 and 60 principal components). The three sets of classification results (i.e., untransformed data, PCA = 60 data, and PCA = 31 data using both the benchmark ANN and DNN classifiers) are listed in Tables 2, 3 and 4, respectively. Please note that in Tables 2, 3 and 4, the first row with the number of hidden layers equal to 10 represents the performance of the traditional benchmark feed-forward ANN.

Comparison of classification results

Once again, the first row in Tables 2, 3 and 4 provides the classification results using the benchmark ANN classifier (with 10 hidden layer neurons), while the remaining rows provide the results from the various DNN classifiers (with the number of hidden layers greater than 10). In each of the three tables, it can be observed that as the number of hidden layers increases from 12 to 28, the accuracy of the classification in the testing phase typically increases, reaching the highest values of 58.6 (in Table 2), 59.9 (in Table 3), and 59.9 (in Table 4) when the number of hidden layers equals 28, 16, and 22, respectively. However, after the number of hidden layers becomes larger than 30 or 35, the accuracy of the classification

Table 1 The ANN classification results using 12 transformed datasets

PCs	Training	Validation	Testing	Overall
1	54.8	53.6	56.8	54.9
3	55.2	53.3	57.3	55.2
6	54.9	53.6	57.3	55
10	56.4	54.6	57.3	56.3
15	56.3	53.3	57.6	56
22	55.2	54.6	58.1	55.5
26	55.1	53.1	58.1	55.2
31	57.5	57.3	*58.1*	*57.5*
34	56.2	56	57.3	56.4
37	55	54.4	57	55.2
40	56.2	56.2	56.2	56.2
60	*57.5*	*54.1*	*58.1*	*57.1*

Table 2 Classification results with ANN/DNN classifiers using entire untransformed data

# of hidden layers	Training (MSE)	Validation (MSE)	Testing (MSE)	Total (MSE)
10	**57.3 (0.3058)**	**53.8 (0.3164)**	**57.3 (0.3124)**	**56.8 (0.3084)**
12	57.5 (0.3055)	54.1 (0.3129)	57.3 (0.3110)	56.9 (0.3074)
14	57.8 (0.3041)	53.8 (0.3127)	57.6 (0.3075)	57.2 (0.3059)
16	58.6 (0.3034)	54.9 (0.3160)	58.1 (0.3099)	57.9 (0.3063)
18	58.2 (0.3045)	53.3 (0.3143)	58.1 (0.3095)	57.5 (0.3067)
20	**59.1 (0.3052)**	**54.4 (0.3186)**	**58.4 (0.3146)**	**58.3 (0.3086)**
22	57.7 (0.3041)	54.1 (0.3169)	58.1 (0.3099)	57.2 (0.3069)
24	57.0 (0.3071)	55.7 (0.3139)	58.1 (0.3066)	57 (0.3081)
26	55.4 (0.3144)	54.9 (0.3245)	58.1 (0.3143)	55.8 (0.3159)
28	54.6 (0.3163)	54.6 (0.3175)	**58.6 (0.3074)**	55.2 (0.3151)
30	54.5 (0.3163)	53.1 (0.3232)	58.1 (0.3215)	54.8 (0.3181)
35	58.3 (0.3050)	54.9 (0.3169)	57.8 (0.3121)	57.7 (0.3079)
40	56.3 (0.3354)	53.3 (0.3584)	57.0 (0.3399)	56.0 (0.3395)
45	58.0 (0.3055)	53.8 (0.3201)	57.0 (0.3113)	57.2 (0.3085)
50	58.3 (0.3034)	53.6 (0.3252)	57.3 (0.3134)	57.4 (0.3081)
100	54.5 (0.3354)	53.3 (0.3353)	57.0 (0.3219)	54.7 (0.3334)
500	55.4 (0.3474)	53.8 (0.3570)	57.3 (0.3386)	55.5 (0.3475)
1000	57.3 (0.3383)	54.1 (0.3521)	57.3 (0.3383)	56.8 (0.3404)

for the testing data stops climbing and drops or converges to values that are close to the results using the ANN classifiers (which includes 10 hidden layers), except for one case where the transformed data with PCs = 60 and the number of hidden layers = 500 is considered. Note that the overfitting issue appears to be under control, in part since all the ANN and DNN classifiers are strictly trained with the same criteria, such that for each classifier the four correction percentages of the classification, corresponding to the training, validation, testing, and entire data sets cannot be significantly different from each other; that is, the absolute value of the percentage difference must be within a defined threshold, for example, 5% (Zhong & Enke, 2017a, 2017b).

It is also observed that after the data are transformed via PCA, the average classification accuracy in the testing phase increases significantly. Moreover, the DNN-based classification using the transformed data with PCs = 31 achieves the highest average accuracy. To verify the phenomena in a statistical manner, a set of paired *t*-tests at the significance level of 0.05 are conducted and the test results are given in Table 5.

Since the P-values of the paired *t*-tests are much less than 0.05, we reject the null hypotheses and conclude that when using the DNN classifiers, the transformed dataset with PCs = 31 produces the highest average classification accuracy, while the DNN classifiers show the poorest performance over the entire preprocessed and untransformed dataset at the significance level of 0.05. Note that the values inside the parentheses in Tables 2, 3 and 4 represent the MSEs for each classification. In general, the higher the correctness percentage, the smaller the corresponding MSEs.

Simulation

While a higher classification accuracy for a financial forecast should lead to better trading results, this is not always the case. Therefore, in this section, a trading

Table 3 Classification results with ANN/DNN classifiers using transformed data with PCs = 60

# of hidden layers	training (MSE)	validation (MSE)	testing (MSE)	total (MSE)
10	**58.2 (0.3062)**	**54.1 (0.3110)**	**57.8 (0.3091)**	**57.5 (0.3074)**
12	56.9 (0.3079)	53.3 (0.3137)	58.1 (0.3066)	56.6 (0.3086)
14	57.9 (0.3041)	54.6 (0.3135)	57.8 (0.3084)	57.4 (0.3062)
16	**59.4 (0.3020)**	**55.4 (0.3128)**	**59.9 (0.3056)**	**58.9 (0.3042)**
18	56.7 (0.3071)	54.6 (0.3109)	58.9 (0.3089)	56.7 (0.3080)
20	58.8 (0.3052)	54.4 (0.3109)	59.2 (0.3074)	58.2 (0.3064)
22	57.3 (0.3065)	55.4 (0.3133)	59.4 (0.3083)	57.3 (0.3078)
24	56.9 (0.3080)	54.9 (0.3099)	58.4 (0.3082)	56.8 (0.3083)
26	55.9 (0.3101)	56.0 (0.3105)	58.4 (0.3088)	56.3 (0.3099)
28	57.8 (0.3057)	56.5 (0.3105)	59.4 (0.3079)	57.9 (0.3067)
30	56.2 (0.3076)	53.6 (0.3152)	58.1 (0.3104)	56.1 (0.3092)
35	56.6 (0.3066)	56.2 (0.3134)	58.1 (0.3081)	56.8 (0.3078)
40	59.8 (0.2999)	54.9 (0.3125)	57.6 (0.3095)	58.7 (0.3032)
45	56.3 (0.3096)	54.6 (0.3163)	57.3 (0.3113)	56.2 (0.3109)
50	55.2 (0.3103)	53.6 (0.3154)	57.3 (0.3078)	55.3 (0.3107)
100	56.9 (0.3077)	53.1 (0.3205)	57.6 (0.3221)	56.4 (0.3117)
500	55.5 (0.3345)	54.9 (0.3309)	**59.9 (0.3162)**	56.1 (0.3312)
1000	58.4 (0.3240)	55.7 (0.3392)	58.1 (0.3285)	57.9 (0.3269)

Table 4 Classification results with ANN/DNN classifiers using transformed data with PCs = 31

# of hidden layers	Training (MSE)	Validation (MSE)	Testing (MSE)	Total (MSE)
10	**56.1 (0.3067)**	**54.4 (0.3121)**	**58.9 (0.3095)**	**56.3 (0.3079)**
12	**61.6 (0.3030)**	56.8 (0.3253)	58.4 (0.3141)	**60.4 (0.3080)**
14	54.6 (0.3237)	54.9 (0.3111)	58.9 (0.3051)	55.3 (0.3190)
16	**61.0 (0.2980)**	**56.5 (0.3087)**	59.4 (0.3084)	**60.1 (0.3011)**
18	54.9 (0.3145)	55.4 (0.3160)	59.2 (0.3091)	55.6 (0.3139)
20	55.0 (0.3096)	56.5 (0.3083)	59.7 (0.3079)	56.0 (0.3092)
22	55.6 (0.3097)	56.8 (0.3120)	**59.9 (0.3059)**	56.4 (0.3095)
24	54.1 (0.3105)	54.1 (0.3133)	58.9 (0.3132)	54.8 (0.3113)
26	56.9 (0.3228)	54.4 (0.3191)	58.6 (0.3125)	56.8 (0.3207)
28	57.1 (0.3049)	54.9 (0.3136)	59.4 (0.3081)	57.1 (0.3067)
30	54.8 (0.3152)	54.4 (0.3142)	58.4 (0.3085)	55.2 (0.3140)
35	58.2 (0.3049)	55.4 (0.3167)	58.9 (0.3083)	57.9 (0.3072)
40	55.3 (0.3111)	54.6 (0.3163)	58.6 (0.3071)	55.7 (0.3113)
45	59.2 (0.3003)	55.7 (0.3147)	58.1 (0.3081)	58.5 (0.3036)
50	57.9 (0.3040)	54.9 (0.3140)	58.4 (0.3070)	57.5 (0.3059)
100	58.6 (0.3044)	54.4 (0.3131)	58.9 (0.3061)	58.0 (0.3060)
500	60.4 (0.3117)	55.4 (0.3436)	58.6 (0.3233)	59.4 (0.3182)
1000	57.7 (0.3237)	56.0 (0.3405)	58.9 (0.3293)	57.6 (0.3271)

Table 5 Comparison of classification results from DNN classifiers for three data sets

Null hypothesis	Alternative hypothesis	P-value
$\mu_{entire} = \mu_{pcs60}$	$\mu_{entire} < \mu_{pcs60}$	1.9144e-04
$\mu_{pcs60} = \mu_{pcs31}$	$\mu_{pcs60} < \mu_{pcs31}$	0.0050

simulation is conducted to see if the higher prediction accuracy from the DNN classifiers indicates higher profitability among the three datasets with different representation. This study is based on predicting the direction of the SPDR S&P 500 ETF (ticker symbol: SPY) daily returns. Consequently, we modify the trading strategy for classification models defined by Enke & Thawornwong ([2005](#)) as follows.

If $UP_{t+1} = 1$, fully invest in stocks or maintain, and receive the actual stock return for the day $t + 1$ (i.e., SPY_{t+1}); if $UP_{t+1} = 0$, fully invest in one-month T-bills or maintain, and receive the actual one-month T-bill return for the day $t + 1$ (i.e., $T1H_{t+1}$).

Here UP denotes the SPY daily return direction as predicted by the models described earlier. In addition, the actual one-month T-bill return for the day $t + 1$ is

$$T1H_{t+1} = \frac{discount\ rate}{100} * \frac{term}{360\ days} = \frac{T1_{t+1}}{100} * \frac{28\ days}{360\ days} = \frac{T1_{t+1}}{100} * \frac{7}{90}, \quad (8)$$

where $T1_{t+1}$ is the one-month T-bill discount rate (or risk-free rate) percentage on the secondary market for business day $t + 1$. The original data for T1 are obtained from the St. Louis Federal Reserve Economic Research database (https://fred.stlouisfed.org/series/TB4WK) and are exactly the "4-week" T-bill discount rate percentage on the secondary market; the data are listed on the website as "Monthly" in terms of the "Frequency" feature of the data but is a 28-day measure.

In practice, at the beginning of each trading day, the investor decides to buy the SPY portfolio or the one-month T-bill according to the forecasted direction of the SPY daily return. It is assumed for this research that the money invested in either a stock portfolio or T-bills is illiquid and detained in each asset during the entire trading day. Dividends and transaction costs are also not considered. In addition, for this study, both leveraging and short selling when investing are forbidden. The trading simulation is done for all the classification models over each testing period, including 376 samples of the three data sets considered; the first day of the 377-day testing period is excluded owing to the lack of a direction prediction for that day. The resulting mean, standard deviation (or volatility), and Sharpe ratio of the daily returns on investment generated from each forecasting model over each set of testing data are then calculated, with or without the PCA involved. The Sharpe ratio is obtained by dividing the mean daily return by the standard deviation of the daily returns. Therefore, the higher the Sharpe ratio, as a result of a higher mean daily return and/or a lower standard deviation or volatility of daily returns, the better the trading strategy. The relevant results are presented in Tables [6](#), [7](#) and [8](#).

As shown in Table [6](#), the trading strategies based on the DNN classifiers for the entire untransformed data generate higher Sharpe ratios than the trading strategy based on the ANN classifier, except for three cases where the number of hidden layers is 40, 50, or 500. In Table [7](#), the trading strategies from the DNN classification over the PCA-represented data with PCs = 60 result in higher Sharpe ratios than the ANN-based trading strategy, except when the number of hidden layers equals 14, 40,

Table 6 Simulation results with ANN/DNN classifiers using entire untransformed data

# of hidden layers	Mean of daily return	Std. of daily return	Sharpe ratio
10	**7.8493E-04**	**0.0077**	**0.1015**
12	7.4376E-04	0.0071	0.1051
14	8.3735E-04	0.0077	0.1090
16	8.2346E-04	0.0078	0.1056
18	1.0000E-03	0.0073	0.1411
20	7.8827E-04	0.0077	0.1030
22	8.4592E-04	0.0077	0.1103
24	8.6660E-04	0.0073	0.1187
26	8.8574E-04	0.0074	0.1196
28	8.3240E-04	0.0075	0.1112
30	8.4049E-04	0.0079	0.1071
35	8.6501E-04	0.0077	0.1119
40	7.9263E-04	0.0079	**0.1006**
45	8.2000E-04	0.0073	0.1125
50	7.7529E-04	0.0077	**0.1004**
100	8.4306E-04	0.0076	0.1110
500	7.9310E-04	0.0079	**0.1007**
1000	7.9541E-04	0.0078	0.1019

45, or 50. Table 8 shows that the Sharpe ratios that are generated by the trading strategies using the DNN classification over the PCA-represented data with PCs = 31 are mostly higher than the Sharpe ratios generated by the ANN-based trading strategy, except for those cases where the number of hidden layers is 12, 24, 26, 45, 50, or 1000. The Sharpe ratios and their corresponding hidden layer numbers that are relevant to these exceptions are highlighted in Tables 6, 7 and 8.

To compare the three sets of Sharpe ratios (17 values in each set) that are obtained from the trading strategies based on the DNN classifiers for the entire untransformed data and the PCA-represented data with PCs = 60 and PCs = 31, another group of paired t-tests are performed at the significance level of 0.05. The P-values of the tests are included in Table 9.

Since the P-values are all much larger than 0.05, we have strong evidence of insignificant differences among the mean Sharpe ratios from the three different trading strategies at the significance level of 0.05. However, with more careful observation of these P-values (and using other significance levels, e.g., 0.40), it is reasonable to conclude that in general the trading strategies guided by the DNN classification based on the PCA-represented data perform slightly better than the ones based on the entire untransformed data, although these trading strategies perform similarly.

Conclusions and suggestions for future work

A comprehensive big data analytics procedure using hybrid machine learning algorithms has been developed to forecast the daily return direction of the SPDR S&P 500 ETF (ticker symbol: SPY). Ideally, researchers look to apply the simplest set of

Table 7 Simulation results with ANN/DNN classifiers using transformed data with PCs = 60

# of hidden layers	Mean of daily return	Std. of daily return	Sharpe ratio
10	**7.6471E-04**	**0.0076**	**0.1011**
12	8.7298E-04	0.0074	0.1178
14	7.0400E-04	0.0077	**0.0911**
16	9.0078E-04	0.0076	0.1181
18	9.0041E-04	0.0075	0.1202
20	9.6420E-04	0.0075	0.1294
22	9.0986E-04	0.0077	0.1188
24	7.8212E-04	0.0076	0.1036
26	9.6026E-04	0.0070	0.1375
28	9.5506E-04	0.0071	0.1354
30	9.3496E-04	0.0074	0.1271
35	7.9479E-04	0.0077	0.1035
40	5.8272E-04	0.0075	**0.0778**
45	7.0538E-04	0.0074	**0.0953**
50	5.9244E-04	0.0071	**0.0832**
100	8.3309E-04	0.0079	0.1061
500	9.3984E-04	0.0074	0.1275
1000	8.7984E-04	0.0076	0.1150

algorithms to the least amount of data, with both the most accurate forecasting results and the highest risk-adjusted profits being desired. We have also considered this standard for this research.

The analytic process starts with data cleaning and preprocessing and concludes with an analysis of the forecasting and simulation results. The comparison of the classification and simulation results is done with statistical hypothesis tests, showing that on average, the accuracy of the DNN-based classification is significantly higher than the PCA-represented data over the entire untransformed data set. More specifically, the DNN-based classification for the PCA-represented data set with PCs = 31 achieves the highest accuracy. It is also observed that as the number of DNN hidden layers increases, a pattern regarding the classification accuracy (as compared to the ANN classifier) emerges, with the overfitting issue remaining under control. In addition, over three data sets with different representations, the trading strategies using the DNN classifiers perform better than the ones using the ANN classifiers in most cases. Although in general there is no significant difference among the trading strategies from the DNN classification process over the entire untransformed data set and two PCA-represented data sets, the trading strategies based on the PCA-represented data perform slightly better.

In previous studies (Zhong & Enke, 2017a, 2017b), the PCA-ANN classifiers are shown to give a higher prediction accuracy for the daily return direction of the SPY ETF for the next day than the FRPCA-ANN classifiers, KPCA-ANN classifiers, and logistic regression classifiers, with or without PCA/FRPCA/KPCA involved. Also, the trading strategies based on the PCA-ANN classifiers perform better than the other strategies based on the other classifiers. Moreover, when using PCA, all classification model-based trading strategies perform better than the benchmark one-month T-bill strategy; the trading strategies from the

Table 8 Simulation results with ANN/DNN classifiers using transformed data with PCs = 31

# of hidden layers	Mean of daily return	Std. of daily return	Sharpe ratio
10	**8.0339E-04**	**0.0076**	**0.1064**
12	7.4933E-04	0.0071	**0.1057**
14	9.3477E-04	0.0072	0.1292
16	9.3504E-04	0.0072	0.1294
18	9.6857E-04	0.0071	0.1359
20	8.0664E-04	0.0072	0.1115
22	9.6978E-04	0.0077	0.1267
24	5.7661E-04	0.0069	**0.0836**
26	7.7980E-04	0.0076	**0.1031**
28	8.5625E-04	0.0078	0.1099
30	8.4888E-04	0.0075	0.1127
35	8.5513E-04	0.0078	0.1093
40	8.2210E-04	0.0076	0.1081
45	7.8532E-04	0.0075	**0.1042**
50	7.1064E-04	0.0077	**0.0922**
100	8.2574E-04	0.0073	0.1126
500	8.9993E-04	0.0077	0.1169
1000	7.9599E-04	0.0076	**0.1050**

ANN classification mining procedure perform better than the benchmark buy-and-hold strategy. Thus, when combined with the new results as illustrated in Tables 2, 3, 4 and 6, 7 8 it can be concluded that among the machine learning techniques considered in this study series, the PCA-DNN classifiers with the proper number of hidden layers can achieve the highest classification accuracy and result in the best trading strategy performance.

With additional hidden layers and more complicated learning algorithms, DNNs are recognized as an important and advanced technology in the fields of computational intelligence and artificial intelligence. However, DNNs are still regarded as a black box with less clear theoretical confirmations of the learning algorithms that are used in common deep architectures, such as the stochastic gradient descent methodology. These DNN learning algorithms actually increase the computation time as a large number of hidden layers and neurons are included. This area of research needs to receive more attention and effort in the future.

Table 9 Comparison of simulation results from DNN classifiers for three data sets

Null hypothesis	Alternative hypothesis	P-value
$\mu_{entire} = \mu_{pcs60}$	$\mu_{entire} \neq \mu_{pcs60}$	0.6251
$\mu_{pcs60} = \mu_{pcs31}$	$\mu_{pcs60} \neq \mu_{pcs31}$	0.8897
$\mu_{entire} = \mu_{pcs31}$	$\mu_{entire} \neq \mu_{pcs31}$	0.6635
$\mu_{entire} = \mu_{pcs60}$	$\mu_{entire} < \mu_{pcs60}$	0.3126
$\mu_{pcs60} = \mu_{pcs31}$	$\mu_{pcs60} < \mu_{pcs31}$	0.5552
$\mu_{entire} = \mu_{pcs31}$	$\mu_{entire} < \mu_{pcs31}$	0.3318

Appendix

Table 10 The 60 financial and economical features of the raw data

Group	Name	Description	Source/Calculation
	Date_SPY	trading dates considered	finance.yahoo.com
	Close_SPY	closing prices of SPY on the trading days	finance.yahoo.com
SPY return in current and three previous days			
	SPYt	The return of the SPDR S&P 500 ETF (SPY) in day t.	finance.yahoo.com / (p(t) - p(t-1))/p(t-1)
	SPYt1	The return of the SPY in day t-1.	finance.yahoo.com / (p(t-1) - p(t-2))/p(t-2)
	SPYt2	The return of the SPY in day t-2.	finance.yahoo.com / (p(t-2) - p(t-3))/p(t-3)
	SPYt3	The return of the SPY in day t-3.	finance.yahoo.com / (p(t-3) - p(t-4))/p(t-4)
Relative difference in percentage of the SPY return			
	RDP5	The 5-day relative difference in percentage of the SPY.	(p(t) - p(t-5))/p(t-5) * 100
	RDP10	The 10-day relative difference in percentage of the SPY.	(p(t) - p(t-10))/p(t-10) * 100
	RDP15	The 15-day relative difference in percentage of the SPY.	(p(t) - p(t-15))/p(t-15) * 100
	RDP20	The 20-day relative difference in percentage of the SPY.	(p(t) - p(t-20))/p(t-20) * 100
Exponential moving averages of the SPY return			
	EMA10	The 10-day exponential moving average of the SPY.	p(t) * (2/(10+1)) + EMA10 (t-1) * (1-2/(10+1))
	EMA20	The 20-day exponential moving average of the SPY.	p(t) * (2/(20+1)) + EMA20 (t-1) * (1-2/(20+1))
	EMA50	The 50-day exponential moving average of the SPY.	p(t) * (2/(50+1)) + EMA50 (t-1) * (1-2/(50+1))
	EMA200	The 200-day exponential moving average of the SPY.	p(t) * (2/(200+1)) + EMA200 (t-1) * (1-2/(200+1))
T-bill rates (in day t)			
	T1	1-month T-bill rate, secondary market, business days, discount basis.	H. 15 Release - Federal Reserve Board of Governors (https://research.stlouisfed.org/fred2/series/DGS5/downloaddata)
	T3	3-month T-bill rate, secondary market, business days, discount basis.	H. 15 Release - Federal Reserve Board of Governors (https://research.stlouisfed.org/fred2/series/DGS5/downloaddata)
	T6	6-month T-bill rate, secondary market, business days, discount basis.	H. 15 Release - Federal Reserve Board of Governors (https://research.stlouisfed.org/fred2/series/DGS5/downloaddata)
	T60	5-year T-bill constant maturity rate, secondary market, business days.	H. 15 Release - Federal Reserve Board of Governors (https://research.stlouisfed.org/fred2/series/DGS5/downloaddata)
	T120	10-year T-bill constant maturity rate, secondary market, business days.	H. 15 Release - Federal Reserve Board of Governors(https://research.stlouisfed.org/fred2/series/DGS10?catbc=1&utm_expid=19978471-Srcl7QpGidAURO4vg_Q.1&utm_referrer=https%3A%2F%2Fresearch.stlouisfed.org%2Ffred2%2Frelease%3Frid%3D18)

Table 10 The 60 financial and economical features of the raw data *(Continued)*

Group	Name	Description	Source/Calculation
Certificate of deposit rates (in day t)			
	CD1	Average rate on 1-month neogtiable certificates of deposit (secondary market), quoted on an investment basis.	H. 15 Release - Federal Reserve Board of Governors
	CD3	Average rate on 3-month neogtiable certificates of deposit (secondary market), quoted on an investment basis.	H. 15 Release - Federal Reserve Board of Governors
	CD6	Average rate on 6-month neogtiable certificates of deposit (secondary market), quoted on an investment basis.	H. 15 Release - Federal Reserve Board of Governors
Financial and economical indicators (in day t)			
	Oil	Relative change in the price of the crude oil (Cushing, OK WTI Spot Price FOB (dollars per barrel)).	Energy Inormation Administration, http://tonto.eia.doe.gov/dnav/pet/hist/rwtcd.htm (work on cleaning the price column first using the SPY dates as control, then cal the relative change)
	Gold	Relative change in the gold price	usagold.com (use FireFox to Select All, then copy and paste to an Excel file) (the dates used by USAGOLD are not matching with the SPY prices from yahoo.finance. For example, after 06/09/2004. We still clean/make up/delete the gold prices based on the dates of SPY prices from finance.yahoo.com. Use the same procedure in the whole data set: Take the average of the two closest data with the missing one in the middle. Then delete the mismatching one, and cal the relatvie difference as before. Another example, the data in 2011, all Friday's prices were recorded as Sunday's prices, so we estimated Friday's prices with the average of Thursday and Sunday's prices. Then deleted Sunday's prices. If there are n continuous values missing, then take the average of the n available values on each side of these n missing values, use the average for all n missing values)
	CTB3M	Change in the market yield on US Treasury securities at 3-month constant maturity, quoted on investment basis.	H. 15 Release - Federal Reserve Board of Governors
	CTB6M	Change in the market yield on US Treasury securities at 6-month constant maturity, quoted on investment basis.	H. 15 Release - Federal Reserve Board of Governors
	CTB1Y	Change in the market yield on US Treasury securities at 1-year constant maturity, quoted on investment basis.	H. 15 Release - Federal Reserve Board of Governors
	CTB5Y	Change in the market yield on US Treasury securities at 5-year constant maturity, quoted on investment basis.	H. 15 Release - Federal Reserve Board of Governors
	CTB10Y	Change in market yield on US Treasury securities at 10-year	H. 15 Release - Federal Reserve Board of Governors

Table 10 The 60 financial and economical features of the raw data *(Continued)*

Group	Name	Description	Source/Calculation
		constant maturity, quoted on investment basis.	
	AAA	Change in the Moody's yield on seasoned corporate bonds - all industries, Aaa.	H. 15 Release - Federal Reserve Board of Governors
	BAA	Change in the Moody's yield on seasoned corporate bonds - all industries, Baa.	H. 15 Release - Federal Reserve Board of Governors
The term and default spreads			
	TE1	Term spread between T120 and T1.	TE1 = T120 - T1
	TE2	Term spread between T120 and T3.	TE2 = T120 - T3
	TE3	Term spread between T120 and T6.	TE3 = T120 - T6
	TE5	Term spread between T3 and T1.	TE5 = T3 - T1
	TE6	Term spread between T6 and T1.	TE6 = T6 - T1
	DE1	Default spread between BAA and AAA.	DE1 = BAA - AAA
	DE2	Default spread between BAA and T120.	DE2 = BAA - T120
	DE4	Default spread between BAA and T6.	DE4 = BAA - T6
	DE5	Default spread between BAA and T3.	DE5 = BAA - T3
	DE6	Default spread between BAA and T1.	DE6 = BAA - T1
	DE7	Default spread between CD6 and T6.	DE7 = CD6 - T6
Exchange rate between USD and four other currencies (in day t)			
	USD_Y	Relative change in the exchange rate between US dollar and Japanese yen.	http://www.investing.com/currencies/usd-jpy-historical-data
	USD_GBP	Relative change in the exchange rate between US dollar and British pound.	http://www.investing.com/currencies/gbp-usd-historical-data (then, take the opposites to the changes)
	USD_CAD	Relative change in the exchange rate between US dollar and Canadian dollar.	http://www.investing.com/currencies/usd-cad-historical-data
	USD_CNY	Relative change in the exchange rate between US dollar and Chinese Yuan (Renminbi).	http://www.investing.com/currencies/usd-cny-historical-data
The return of the other seven world major indices (in day t)			
	HSI	Hang Seng index return in day t.	finance.yahoo.com
	SSE Composite	Shang Hai Stock Exchange Composite index return in day t.	finance.yahoo.com
	FCHI	CAC 40 index return in day t.	finance.yahoo.com
	FTSE	FTSE 100 index return in day t.	finance.yahoo.com
	GDAXI	DAX index return in day t.	finance.yahoo.com
	DJI	Dow Jones Industrial Average index return in day t.	finance.yahoo.com(no download function for this one); measuringworth.com/datasets/DJA/result.php
	IXIC	NASDAQ Composite index return in day t.	finance.yahoo.com
SPY trading volume (in day t)	V	Relative change in the trading volume of S&P 500 index (SPY)	finance.yahoo.com
The return of the eight big companies in S&P 500 (in day t)			
	AAPL	Apple Inc stock return in day t.	finance.yahoo.com
	MSFT	Microsoft stock return in day t.	finance.yahoo.com

Table 10 The 60 financial and economical features of the raw data *(Continued)*

Group	Name	Description	Source/Calculation
	XOM	Exxon Mobil stock return in day t.	finance.yahoo.com
	GE	General Electric stock return in day t.	finance.yahoo.com
	JNJ	Johnson and Johnson stock return in day t.	finance.yahoo.com
	WFC	Wells Fargo stock return in day t.	finance.yahoo.com
	AMZN	Amazon.com Inc stock return in day t.	finance.yahoo.com
	JPM	JPMorgan Chase & Co stock return in day t.	finance.yahoo.com

Abbreviations
ANN: Artificial Neural Network; DNN: Deep Neural Network; PCA: Principal Component Analysis

Availability of data and materials
Upon publication, publication data will be made available at http://web.mst.edu/~enke/main_publications.html and/or the Missouri University of Science and Technology Scholars Mine data repository (http://scholarsmine.mst.edu/).

Authors' contributions
XZ contributed to the neural network model development and coding, input dataset preprocessing, model testing, and trading simulation. DE contributed to the neural network model development, input data selection, and trading strategy development. Both authors read and approved the final manuscript.

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Both authors give their approval and consent to participate.

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