Comparison of Sentiments Data Extraction and Prediction

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Abstract. Exponentially increasing amount of information, variety of data forms, growing number of big data analysis ant prediction tools give the new opportunities for business but create needs for right decisions of selection. This study aims to make three-dimensional analysis of data extraction methods, forecasting methods and sentiment indexes. Historical numerical data and textual data from forex news expressed throw the two sentiment indexes are forecasting by econometric methods, Python text analysis and unique computational intelligence tool. Prediction of ensemble of *Evolino* recurrent neural networks (EERNN) is a distribution of expected values reflecting the probabilities of different states of market sentiments. The results are intended to individual investors needs and give them opportunity of choice, which depends on what data is available, the accuracy of the prediction, how much time can be taken to make the prediction and that the forecaster has enough skills to use the appropriate IT tools.

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Short title: Sentiments data.

Introduction

Effectively investing in real market which often does not comply with the effective market hypothesis requires the selection of reliable forecasting tools. Well-known econometric forecasting methods are common and frequently used to predict economic processes. There is a huge amount of text information in social media; social networks create opportunities for investors to quantify opinions and use data to make predictions. The forecasting algorithms based on artificial intelligence can be successfully integrated into business intelligence systems. The comparison of different forecasting tools enables investors to choose the best method to evaluate market irrationality and use the corresponding prediction method. Sentiments of individual investors are used as a contrarian indicator for exchange rates or finance index action. Predictions of the sentiments provide additional information for investors and can lead to better decisions in the financial markets.

Investors are a group of people directly related to the market rationality and irrationality. Investors express their expectations, views and approaches of market processes using the internet, forums, surveys and realistic market actions. Different aspects of investor behaviour were investigated. Pompian [1] identifies four categories of investors: the preserver, the follower, the independent and the accumulator, - each of whom has distinct behavioural biases and risk profiles. Grinblatt et al. [2] analyse whether IQ influences trading behaviour, performance and transaction costs. Merkle and Weber [3] combine the survey data about return expectations, risk expectations and risk tolerance with investors' actual trading data and portfolio holdings. The authors found that the behaviour of investors has multiple characteristics; many different factors play significant roles in investment decisions. The search of information plays a significant role in investment decision-making. Ozsoylev et al. [4] investigated an empirical information network of investors and found out that central investors earn higher returns and trade earlier than peripheral investors with respect to information events.

Studies about why some investors are successful, and the others should choose a different career path often provide conflicting answers. Crongvist et al. [5] investigated the behaviour of investors and found that investors' styles have a biological basis and are partially ingrained from birth, and that investors' styles also depend on previous investor experience. Li et al. [6] studied the differences between institutional and individual investors and found that institutional investors are better informed, trade more selectively and react asymmetrically to up-and-down-market movements. Less informed individual investors allocate their investments evenly across stocks, and they are more influenced by market sentiment and attention-grabbing events.

Investors' opinions are important in trading activities be-

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cause they are the main factor that influences their behaviour in the financial market. Sentiments of investors are positive and negative opinions ratio. Measuring the sentiments is important for selecting an informative data set for prediction. Preis et al. [7] suggest that Google Trends data and stock market data may reflect two subsequent stages in the decision-making process of investors.

Research on investment in finance uses different sources of sentiment data. The most popular data come from social media: StockTwits [8, 9, 10] and text analysis [11, 12, 13]. Data for predictions of the stock or exchange market are also used by constructing sentiment indices based on a survey of investors, Facebook's Gross National Happiness Index [14].

Attempts to predict stock returns, volatility and trading volume are very controversial. The findings of Corredor et al. [15] show that sentiment has a significant influence on returns, varying in intensity across markets. Kim and Kim [16] discovered evidence that investor sentiment is positively affected by prior stock price performance. Chen et al. [17] discovered that a younger, speculative industry fits in a linear local sentiment-returns model but an industry with experience fits in a nonlinear and asymmetrical prediction of sentiments and returns. Liu [18] found out that the stock market is more liquid when sentiment indices rise, that is when investors are more bullish. Albu et al. [10] investigated a possible connection between the asymmetric volatility and the dynamics of two sentiment indices. Aboura [19] found that an individual investor's sentiment index is more informative when financial markets are bearish. To summarise, it could be stated that there is no evidence that analysts' opinions presented in the news media accurately predict subsequent stock returns. This contradiction of findings is based on different measures of sentiments, different selection of data and different prediction time. Sentiment indices cannot be used as leading indicators of financial market changes, but information about sentiments can be used in other ways. Linardos et al. [20] proposed an innovative system, combining information from news releases and technical indicators in order to enhance the predictability of the daily stock price trends, and experimental results confirm the aforementioned impact. Azar and Lo [21] developed a simple hypothetical trading strategy, based on the content of tweets, which outperformed several benchmarks.

Predicting the sentiment indices can help investors develop new strategies for trading. The simplest way to predict the sentiments of individual investors is to use well-known econometric methods. Sentiment analysis by text classification is used to measure investors' sentiments and can be used as an indicator of information from the media. Dougal et al. [22] measured the media's conditional effect. This increases explanatory power by one-third and identifies amplification or attenuation of prevailing sentiment as a tool used by financial journalists. Oliveira et al. [23] verify the statistical relationship between some sentiment variables and each stock return, volatility and trading volume. The authors found some evidence that the volume of *Twitter posts* is relevant for modelling the next day trading volume. Sprenger et al. [24] found the sentiment (i.e. bullishness) of tweets to be associated with abnormal stock returns and message volume to predict the next-day trading volume.

Algorithms based on artificial intelligence use data of sentiments for input like teaching data to predict the finance variables. Ho and Wang [25] developed an Artificial Neural Network (ANN) model using new sentiment analytics to predict the stock price movements. Chen et al. [26] proposed a nonlinear, autoregressive model with exogenous sentiment inputs to predict stock price movement.

Piñeiro-Chousa et al. [27] used a model based on artificial intelligence to investigate financial variables and variables related to social media activity, such as number of tweets, number of followers or the experience of the users.

The aim of this paper is to compare text classification and artificial intelligence-based forecasting tools with well-known econometric forecasting methods. By extracting the advantages and disadvantages of forecasting, evaluating the accuracy will allow investors to choose the most appropriate investor sentiment forecasting method or a combination thereof.

1. Materials and methods of sentiment forecasting

The opinion is the main characteristic of human behaviour, and sentiments are the ratio of positive and negative opinions. This research investigates the sentiments of individual investors, such as the expectations that guide their behaviour. Two different measures are used for prediction: the sentiment survey from the American Association of Individual Investors (AAII) [28] and the speculative sentiment index (SSI) [29].

The AAII Sentiment Survey asks a simple question to more than 170,000 members of the AAII: "I feel that the direction of the stock market over the next six months will be: Up-Bullish; No Change-Neutral; Down-Bearish" [30]. Useful measures for prediction are the difference between bullish and bearish sentiments and logarithmic function of the bullish and bearish ratio. Rotblut's [31] studies have shown that American individual investors' sentiments can be used as an indicator of the stock market, especially for long-term financial goals.

The SSI includes data obtained from real investors with actual positions. SSI is the ratio of long to short positions in the exchange rate or stock index. The SSI is useful for the larger imbalances. A good rule of thumb is to look for readings of greater than +2 or less than -2 in which the trend agrees with the contrarian element of the indicator. The SSI is used as a contrarian indicator to price the action of exchange rates: EUR/USD (euro and United States dollar), USD/JPY (United States dollar and Japanese yen), GBP/USD (Great Britain pond and United States dollar), AUD/USD (Australian dollar and United States dollar), XAU/USD (gold prices and United States dollar) and the stock index SPX500.

Weekly data of sentiments were used to examine three very different groups of forecasting tools: econometric methods, text classification and artificial intelligence.

Econometric methods. Econometric forecasting methods are based on a paradigm that the future is a continuation of the past. One of the main advantages of these methods is their universality. Econometric methods are used for stocking prices, exchange rates and other financial instruments. Moving averages (MA) are the most commonly used financial market forecasting tools. The Simple Moving Average (SMA), Weighted Moving Average (WMA), and Exponential Moving Average (EMA) show tendency of price fluctuation based on point prediction. Trends also predict one point in the future. Regression function is selected by the determination coefficient. Bollinger bonds determine interval for predicting the price. Econometric methods are simple to use, and they do not require special skills or information technology resources.

Sentiment analysis by text classification. Investors in financial markets pay attention to economic and political news, and they share information and insights with each other. It is difficult to cover the large output of information. The investor's job is to monitor market news and data, choose what is important at the moment and make a good trading decision. Market news and information is available through a multitude of sources. The Internet is an obvious source, and free content is available on many special market websites, servers and TV programmes. Text classification can help to classify the text according to whether it represents a positive mood, negative mood or neutral mood. Natural text processing is made by the Python algorithm with text tokenization and using WordNet [32]. WordNet is a large lexical database that is an important tool in computational linguistics and natural language treatments. Brief news items from marketpuls webportal [33] were selected as they provide a concise view of the best known, real-time information sources (CNN, Bloomberg, Reuters, MarketWatch and others). Prediction of sentiments by text classification is based on the paradigm that the future is a result of events that occurred in the past. Political and economic news report the events that influence the opinions of investors.

Artificial intelligence based forecasting. Algorithms of artificial intelligence simulate the intelligent human activities. Forecasting or foresight is one of the most important intellectual activities. In 2005, Shmidhuber et al. [34] proposed the new class recurrent neural network algorithm *Evolino* (EVolution of recurrent systems with Optimal LINear Output). This recurrent neural network was adopted for forecasting of finance markets by the correct choice of parameters such as the number of neurons, the number of epochs, the

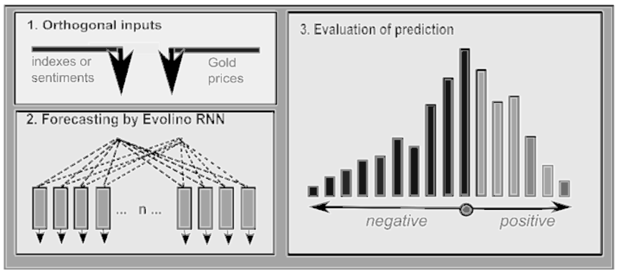

Fig. 1. Prediction model based on *Evolino* RNN (Source: created by authors).

amount of data and their relationship with the training data for predictions of financial markets [35]. Later we constructed the ensemble from 176 *Evolino* with two orthogonal inputs [36, 37] and tested it to predict exchange rates. The scheme of the prediction model is shown in Fig. 1.

Historical data of AAII and SS indexes of sentiments is using for the first input. The second input is the historical data of gold prices in American dollars (XAUUSD). Orthogonality of the inputs makes predictions more accurate and prediction times shorter [38]. Forecasting is done by 176 *Evolino*, and each of *Evolino* uses a different historical data set. The result is the distribution of the expected values of sentiments. The prediction is evaluated according to the last known value of the sentiment index and by calculating the probabilities of the expected change of sentiments. Prediction by ensemble of *Evolino* RNN (EERNN) is based on the paradigm that the future is the distribution of opportunities.

Three different groups of forecasting tools can be compared in data mining: overall classifier accuracy, forecasting errors and complexity of process. Overall classifier accuracy is expressed as ratio of true predictions of directions of sentiments change and total number of predictions.

2. Forecasting of sentiments

All selected forecasting methods were used for forecasting the AAII data and the SSI data of EUR/USD, GBP/USD, USD/CHF and USD/JPY from 11 January 2016 to 21 April 2016. Forecasting by ensemble of *Evolino* RNN was done only for AAII because the SSI data were insufficient.

Forecasting by SMA, WMA, EMA, BB and trend did not require a big set of data or special skills of a decision-maker, and the length of time taken to complete the forecasting process does not matter.

The *text classification* method to predict the sentiments of individual investors was tested by online sentiment analysis with Python NLTK text classification on positive, negative and neutral sentiments [32]. The daily financial market news flow is huge, but it is difficult to find texts that are subjective. This means that to find positive or negative sentiments in the texts of daily news is difficult because journalists are trained to write objective articles that don't have a negative or a posi-

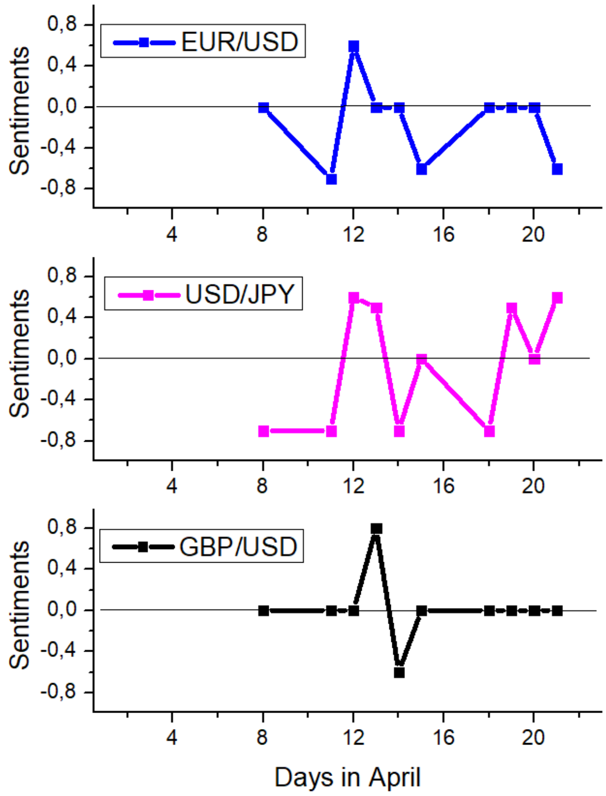

Fig. 2. Dynamics of sentiments of news is about three main exchange rates - EUR/USD, USD/JPY and GBP/USD.

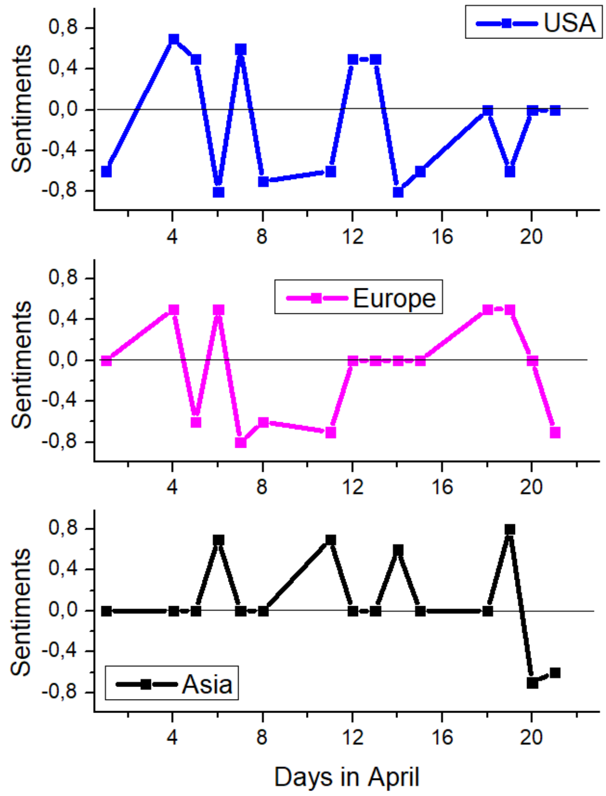

Fig. 3. Dynamics of sentiments of news shows the USA, Europe and Asia markets.

tive bias. Therefore, sentiment may be more visible on social networks and blogs, where opinions are more often and obviously expressed. On the other hand, if the text has polarity (positive or negative), it is appropriate to point out because it means that even journalists cannot convey new information without a subjective opinion which is really important.

Daily sentiments of news about the three main exchange rates - EUR/USD, USD/JPY and GBP/USD - are presented in Fig. 2. Sentiment analysis from website text-processing [32] uses a hierarchical classification of a combination of subjective classification and polarity classification. The first step is to use subjectivity classifier that determines whether the text is objective or subjective. If the text is objective, then the sentiment is given 0 value and polarity classification is not used. However, if the text is subjective, then the polarity classification is used to determine whether the text is positive or negative. Negative sentiments are evaluated on a scale of $[-1 \div 0)$ and positive sentiments on a scale of $(0 \div 1]$.

Neutral sentiments are indicated by a dashed line, positive sentiments are indicated above this line, and negative sentiments are indicated below this line. Another way of evaluating text sentiments is to group news according to the economic zones of the USA, Europe and Asia - see Fig. 3.

Economic indicators such as interest rates, employment, gross domestic product (GDP) and the European Central Bank and federal reserve systems affect the capital market sentiments because the variety of financial market news runs the stock indices courses. News about these events is published every day. Sentiments of US economic zone vary the most, and the Asia zone sentiments - the least. A visible trend is that news with positive sentiments changes to negative sentiments the next day and vice versa. Daily sentiments are summarised into weekly data and compared with real AAII data and SSI data of exchange rates and stock indices.

Investors have their own language, so it is appropriate to establish a text classification programme to use specifically for financial market sentiments. The idea came from the fact that the analysis of articles on the currency pair of the British pound sterling and the US dollar found that one of the most relevant topics was Brexit (British withdrawal from the European Union). The paragraph, about the British withdrawal from the European Union, also projected the country's national currency exchange rate loss. However, sentiment analysis using text classification links these paragraphs to a positive sentiment.

Artificial intelligence. During the same ten weeks, the AAII sentiments were predicted by the EERNN. Predictions were made by analysing the histograms of expected values according to the value of the previous week. The data from the AAII is presented in $\log_2$positive/negative scale. 400 numbers represents the minimal length of time series. Three histograms of April 2016 are presented in Fig. 4.

The main part of this histogram is right of the last known value (black line), so the prediction means that sentiments

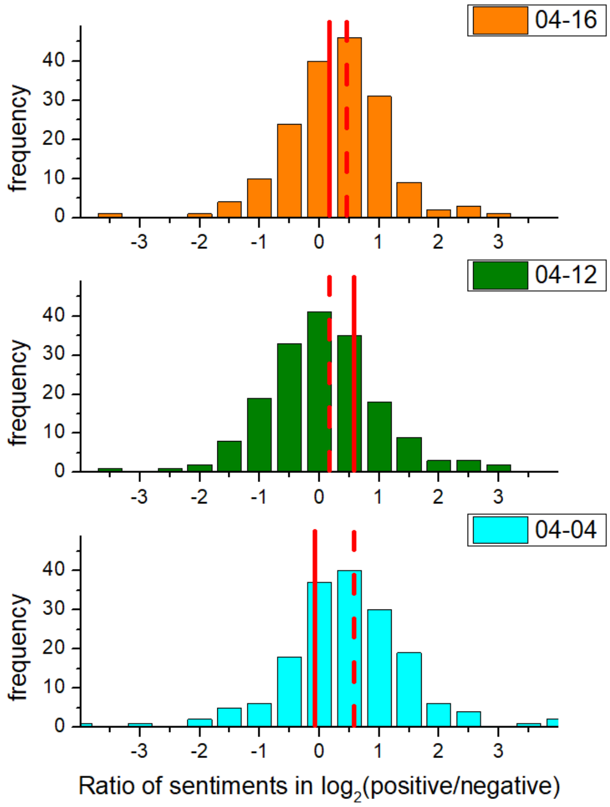

Fig. 4. Evaluation of prediction of AAII sentiments by ensemble of *Evolino* RNN 04 April 2016; 12 April 2016; 16 April 2016. Black line represents last known value, dashed line – real value.

will become more positive. The probability that the sentiments will grow is 59%; the probability that the sentiments will decrease is 41%. The dashed line represents the real value of the sentiments of that week. The EERNN correctly predicted not only a change in direction of sentiments but value of sentiments too.

For next week predictions (12-18 April 2016, see Fig. 4), the main part of the histogram and mode is left value of the previous week (black line). More negative sentiments are a clear prediction of this week. The probability of more positive sentiments is 40% and more negative is 60%. The real value (dashed line) shows that the direction of change of the sentiments was predicted correctly and the mode value has been reached.

For third week predictions (19-26 April 2016, see Fig. 4), the growth of positive sentiments occurs, and the mode of the histogram coincides with the actual value of the week. So the prediction is accurate enough. The probability of sentiment growth is 54%; the probability of a decrease in sentiment is 46%. Prediction sentiments by EERNN are informative and easy to interpret but they require information technology resources.

3. Comparison of forecasting methods

Sentiment data generated on the internet has been increasing rapidly. Data mining is a process that leads to better decision-making. Data are based on surveys of individual investors' opinions, the AAII and the decisions of individual investors, and the SSI is simple to use in numerical form. Econometric methods and algorithms of artificial intelligence require time series data. The text classification method depends on the selection of data in text form. The amount of data is not enough to get predictions using econometric methods, but the AI model uses about 60÷100 points of the data range. Every day, 2-3 pages were used to find sentiments in the finance news. It was difficult to select the information from the huge flow of news.

Sentiment analysis is based on classification of sentiments into positive, neutral and negative. Sentiments changing direction is usually more important for decision-making than prediction of the real value. The comparison of overall classifier accuracy of investigated forecasting methods is presented in Table 1.

The overall classifier accuracy of AAII data forecasting is equal to 1 only for ensemble of *Evolino* RNN, which means that all predicted directions were right. The SMA and WMA methods correctly predicted the sentiments 9 out of 10 weeks, BB correctly predicted 8 out of 10 weeks and text classification correctly predicted 7 out of 10 weeks. The forecasts using other methods were incorrect. Econometric methods predicted the SSI data with very weak accuracy; only BB and trend exceeded 50%. MAE, MAPE and RMSE measured the accuracy of predictions of the AAII and SSI data. The comparison of forecasting errors is presented in Table 2.

Table 1. The comparison of overall classifier accuracy (OCA) (originally created by authors)

	AAII OCA	AAII range	SSI OCA	SSI range	Range total
SMA	0.9	II-III	0.4		III-IV
WMA	0.9	II-III	0.4		III-IV
EMA	0.4		0.5		VII
BB	0.8	IV	0.6	I-II	II
Trend	0.5		0.6	I-II	V
Text classification	0.7	V	0.5		VI
EERNN	1	I			I

Table 2. The comparison of errors of forecasting (originally created by authors)

	MAE AAII	MAPE AAII	RMSE AAII	MAE SSI	MAPE SSI	RMSE SSI	Range total
SMA	3.80	11.90	4.53	0.49	121.23	0.59	IV
WMA	3.47	10.90	4.13	0.46	112.72	0.55	III
EMA	4.55	14.80	5.29	0.54	138.3	0.61	V-VI
BB	3.32	10.54	4.13	0.23	101.91	0.29	II
Trend	7.56	24.76	9.19	1.91	219.25	2.15	VII
Text classification	6.03	10.39	8.09	0.83	181.75	1.02	V-VI
EERNN	0.09	3.92	0.11				I

Forecasting methods according to errors of forecasting occurred in the following order: AI, BB, WMA, SMA, EMA, text classification and trend.

The complexity of forecasting using the investigated methods is different. The econometric methods are simple to use, and they are sufficient for basic computer literacy. The text classification method predicted using online sentiment analysis with Python NLTK text classification. This tool is simple to use but requires time for data selection and evaluation. The ensemble of *Evolino* RNN requires the skills of information technologies for data preparation, running and interpretation of forecasting. The forecasting time was about 4-5 hours, and the sources of IT included 8 processors.

5. Conclusions

The uncertainty of financial markets is one of the key aspects to which all participants in the financial markets must adapt. The most important factor in determining the uncertainty in the market is the limitation of rationality. Investors' rationality is affected by various psychological factors, so sentiment forecasting can provide additional information for investment decision-making.

To evaluate investors' sentiments, data were selected from individual investors' surveys: the AAII and SSI. Investors' sentiment has been predicted using three completely different types of methods: econometric, text classification and algorithms based on artificial intelligence. The innovative model based on artificial intelligence and tested early in the prediction of exchange rates was adopted to forecast the individual investors' sentiments and create new opportunities for investors.

The overall classifier accuracy of the AAII by all forecasting methods except the trend exceeds 50%. Only the ensemble of *Evolino* RNN guessed correctly the sentiments change in direction in 100% in ten weeks of testing. The SSI data was predicted with very weak overall classifier accuracy: only BB and trend exceeded 50%.

Forecasting methods according to errors of forecasting (MAE, MAPE, RMSE) occurred in the following order: AI, BB, WMA, SMA, EMA, text classification and trend.

Choosing a sentiment forecasting method depends on the availability of the data, the accuracy of the prediction, time to be taken to make the prediction and that the forecaster's skills to use the appropriate IT tools. Each of the tested prediction methods can be used to develop a trading strategy by combining them with the other trading indicators. These studies can be applied to the activities of investment funds.

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