Neurocomputing 275 (2018) 1150–1159

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom

On neural networks and learning systems for business computing

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ARTICLE INFO

Article history:
Received 5 August 2017
Revised 10 September 2017
Accepted 18 September 2017
Available online 22 September 2017

Communicated by Hu Jun

Keywords:
Neural networks
Deep learning
Machine learning
Business activities

ABSTRACT

Artificial intelligence, including neural networks, deep learning and machine learning, has made numerous progress and offered new opportunity for academic research and applications in many fields, especially for business activities and firm development. This paper summarizes different applications of artificial intelligence technologies in several domains of business administration. Finance, retail industry, manufacturing industry, and enterprise management are all included. In spite of all the existing challenges, we conclude that the rapid development of artificial intelligence will show its great impact on more fields.

1. Introduction

Artificial intelligence (AI) has made numerous progress and become more and more important in recent years. This is due to its wide applications in many fields such as computer vision, speech recognition and economics. It even creates some new subjects which combine the traditional ones and new technologies together, including intelligent diagnosing and treatment. To resolve more complex problems, a great number of tools including neural networks, deep learning and machine learning have been developed by AI.

Neural network consists of an interconnected group of artificial neurons, while deep learning, a method of machine learning, has developed several layers on the basis of neural networks. Neural networks have emerged in the past decades as an area of new opportunity for academic research and applications, all these applications which aim to solve plenty of real world problems are seen as artificial intelligence. Deep learning, which is based on neural networks with more layers added, aims to find the rules, modes and hidden relationships from the big data, in the way of using neural networks to learn relevance between repeatedly. Machine learning has also occupied an important position in artificial intelligence with a long history of over 50 years. The algorithms allow computers to follow human's actions and improve their performance continuously via learning new knowledge or technologies. Such a technology is the core of artificial intelligence, for that it focuses on imitating how human think and study with the essential way.

Artificial intelligence has also been viewed as a huge breakthrough technology which can change business models [1]. Many people believe that utilizing artificial intelligence will help firms to acquire competitive advantages in providing new products and services, while improving immense productivity [2].Actually, many areas in business have already been greatly transformed by artificial intelligence, including finance (et. banking industry [3]), social commerce [4], predictive analytics [5], macroeconomic measurement and forecasting [6], and business intelligence and analytics (BI&A) [7].

Taking intelligent manufacturing as an example, a team from Intel has ever applied ANN-GA algorithm to manage ready-mixed concrete enterprises and decrease relative errors of concrete compressive strength of one kind of concrete to 3% [8]. Besides, there are more and more firms using artificial intelligence and big data to find new business opportunities [9] and make marketing mix frameworks [10]. Consequently, different aspects of artificial intelligence, including neural networks, machine learning, deep learning and knowledge graph, have overthrown the traditional business models.

Based on the analysis above, we believe that there still exists great chance for artificial intelligence technologies to be applied

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https://doi.org/10.1016/j.neucom.2017.09.054
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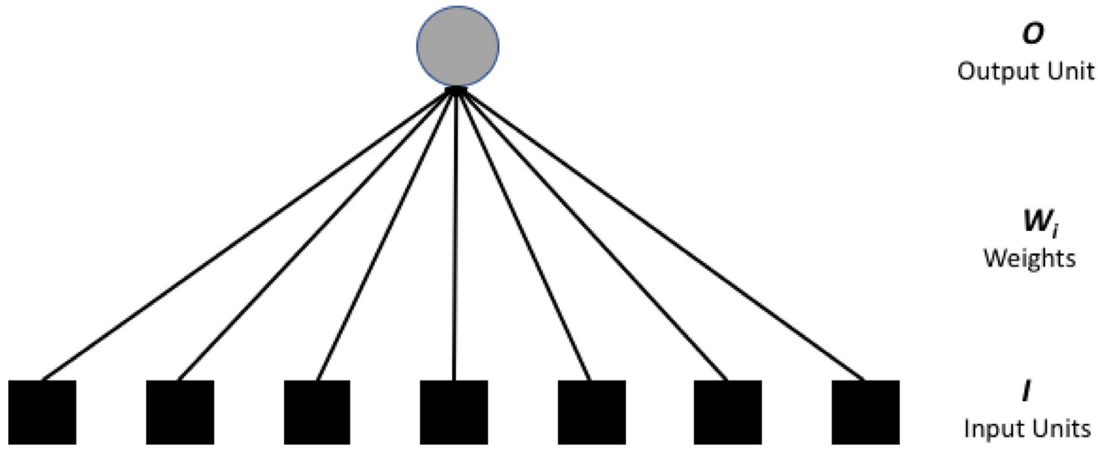

$$O = \sigma\left(\sum_{i=0}^{n} W_i X_i\right)$$

Fig. 1. Graphical representation of perceptron.

in business activities. Those technologies can help firms to make most rational decisions, solve difficult problems and improve their performance. Although many scholars have tried to apply artificial intelligence technology in business activities, there is a lack of summary about what kind of artificial intelligence technology is fit for the specific area, and how do the decision-making process be optimized by this technology. Therefore, making a review about the effects of the branches of artificial intelligence (neural networks, deep learning, machine learning) on business decisions is necessary for the future research and development of computer advanced technologies which are used in the management of firms. Thus, we believe this paper would shed light on the interdisciplinary collaboration between business administration and artificial intelligence which has broad prospects.

In this paper, we will present a survey of AI with applications in business activities. The rest of this paper is organized as follows. From section two to five, the applications of neural networks, deep learning and machine learning will be discussed seriatim. The references discussed in this paper include, but are not limited to the following aspects: (1) The technology of neural networks for enterprise management, finance, manufacturing and retail industry, medical, military; (2) The technology of deep learning for solving financial prediction problems, developing marketing strategies; (3) The technology of machine learning for bankruptcy prediction, housing price prediction and business administration; (4) Other business intelligence for supply chain management, risk management, intelligent transportation and sharing economy. In section six, we will draw a conclusion and discuss the current difficulties and challenges. The last section will be the future research directions.

2. Neural networks for business activities

Neural networks technology is gradually becoming a common choice with its influence spreading to a growing number of domains. Researchers have designed different kinds of neural nets systems for their own satisfaction. As is shown in Fig. 1, perceptron is a feed-forward network with only one layer of learnable weights connected to one or more units, which is the basic element of neural network. Perceptron is a linear classification algorithm of supervised learning. An activation function is used to reach the goal of nonlinearity. It combines a set of weights with the feature vector to make predictions. Perceptron can date back to the middle of last century and therefore it's regarded as one of the earliest machine learning algorithms in the world.

Artificial neural network is a generalization of simple perceptrons, so it's also called multi-layer perceptrons (MLP). The example in Fig. 2 contains three layers of neurons, which is the minimum requirement. Artificial neural network becomes so popular mainly because of the backpropagation method, which adjusts weights to optimize the performance of the nets using the gradient of the loss function. In theory, one-hidden-layer neural nets can approximate any functions. But more layers are often added to accelerate the learning process.

According to Ahmad et al. (2015) [11], the neural network and fuzzy logic have been used to measure and forecast the Intellectual Capital. From the ANFIS simulation results, the results of the model have been proved to be convenient for innovation forecasting. A linear discriminant analysis which is based on backpropagation learning algorithm and backpropagation neural network models have been developed to evaluate the firms' performance, the results show that backpropagation neural networks are not superior to LDA-models (Linear Discriminant Analysis) [12]. Neural networks technology has also been used to set up a decision support system [13], assess task duration in investment projects [14], calculate the connections between different factors with wealth creation [15] and predict corporate bankruptcy [16–18]. Many other methods based on neural networks, such as back propagation (BP) neural networks [19], adaptive neuro-fuzzy inference system (ANFIS), structural equation modeling (SEM) [20–22] have been used to forecast or evaluate the performance of a firm.

The self-organizing map (SOM) approach has been used to monitor Global Entrepreneurship. After the authors have analyzing 45 countries from 2005 to 2006, several patterns about entrepreneurial opportunity recognition have been revealed [23]. Many other researchers pay close attention to quantifying the connectivity between different determinants and organizational innovation [24], making small-business credit scoring model [25].

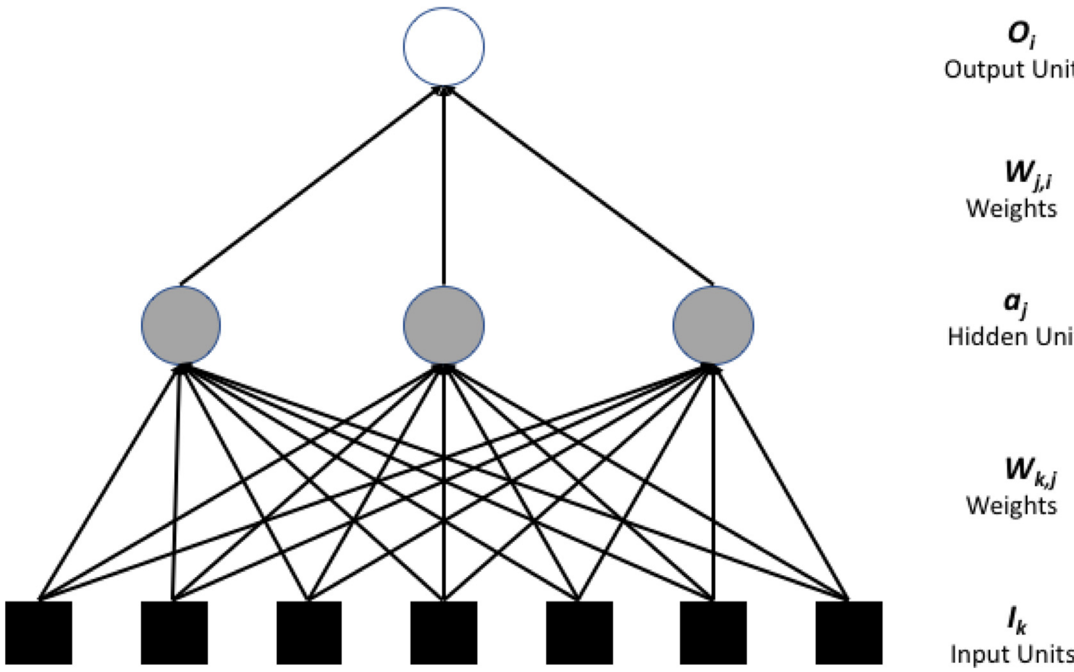

Fig. 2. Graphical representation of multi-layer perceptrons.

Firms' innovative performance in Korea has also been studied. Based on Bayesian network, the impact of innovative performance has been analyzed [26].

Researchers have also summarized many different applications about how neural networks being used in the field of finance [27]. According to Michal Tkáč and Robert Verner's research, several hybrid networks have been widely used in solving financial problems of distress or bankruptcy, and forecasting stock price [28–36]. As Namazi et al. (2016) stated [37], the neural networks have been used to overthrow a traditional financial empirical opinion. It has been found that the most important factors in determining free cash flows (FCF) risks are profitability, debt policy and firm size. This study with the data of 1224 firms from Tehran Stock Exchange (TSE) in the first decade of this century has proved that Jensen's point of view in 1986 (managers with more FCF available behave opportunistically) is wrong. According to Hossain and Nasser (2008) [38], a generalized autoregressive conditional heteroskedastic (GARCH) model has been developed to replace Autoregressive (AR) model as well as other models which are frequently used in financial time series prediction. Comparing with four international stock markets indices, it shows that the GARCH model achieves better results.

Manufacturing industry analysis has also received extensive attention by using the technology of neural networks. To measure the innovation performance of Taiwanese manufacturing industry, an adaptive neuro-fuzzy inference system (ANFIS) has been implemented [39]. Saoussen Boujelben takes Tunis, a developing country (or region) as the research object, and gets the conclusion that occasional R&D (research and development) activities are more efficient in manufacturing [40]. Via neural networks, manufacturing firms in Malaysia can predict how the knowledge management (KM) affects manufacturing performance [41].

Neural clustering and classification networks system is also used to forecast sales of new apparel items. Sébastien Thomassey has proposed such a decision aid system [42]. Using real data from French textile distributor, it is able to automatically and precisely evaluate the performance of textiles and apparel. Penpece D has ever tried to use multi-layer perceptron (MLP) to analyze the sales revenue of Turkish grocery retailing industry, which based on the data of marketing costs, gross profit and other features [43].

Some other fields have also been concerned, such as tax, accounting [44], credit card application assessment [45], portfolio management, financial prediction and planning [46], fraud detection [47], time series forecasting [48], data mining [49]. Doctor Razieh Tabandeh has made the conclusion that unemployment is very important in the causes of tax evasion, with the data from Malaysian government in fifty years [50]. Heath industry is also an important field in neural networks. Chen has tried to use neural networks to study the US pharmaceutical firms and explore influences of many factors upon their patent citations [51]. In the area of military, Erkollar Alptekin has put a so-called adaptive neuro-fuzzy inference systems (ANFIS) approach forward to make adjustment to military education resources allocation [52].

3. Deep learning for business activities

With more layers, deep learning is becoming increasingly important in practical applications. When handling data with multiple levels of abstraction, it allows computational models to learn the representations better [53]. Deep learning is also known as representation learning, which can be the solution to learning problem of neural networks that have more than one hidden layer. Not only neural networks can be used to construct deep learning tasks, but also other techniques like random forest are able to do this. To some extent, deep learning makes machine learning much closer to the goal of artificial intelligence. The graphical representation is presented in Fig. 3:

Standard supervised backpropagation is a basic way of deep learning. Many researchers came up with different ideas and compared them. Jason Weston has presented a nonlinear semi-supervised embedding algorithm which have less error rates than some techniques similarly based on shallow semi-supervised, when being applied in deep multi-layer architectures [54].

Deep learning algorithms, especially deep convolutional nets and recurrent nets, have gain unprecedented progress in many places, including images (especially face recognition), video,

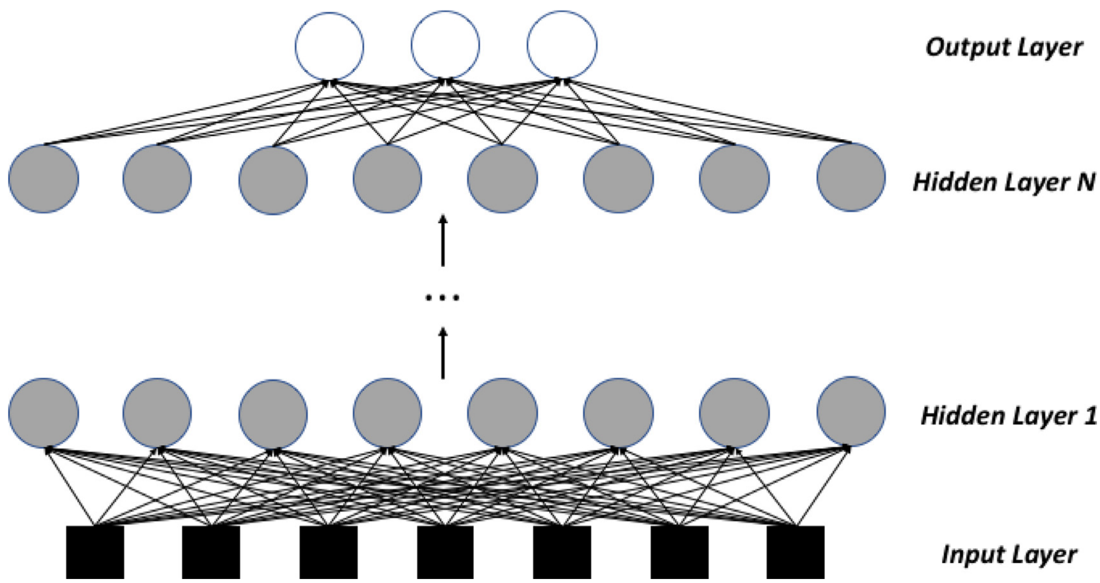

Fig. 3. Graphical representation of deep learning using artificial neural network.

speech, text and so on. Actually, in technical field, deep learning and its variants have been confirmed to be effective in recognition, visual object recognition and object detection. Meanwhile, the genomics, drug discovery, finance, vehicles' autonomous driving, plant biometric system [55], energy efficiency evaluation, data representation learning [56] and many other domains are also benefited from the development of deep learning.

Deep learning algorithms are also proved to be useful in solving financial prediction problems and exploiting interactions of data, which is impossible to be explained by all existing financial economic theories [57–59]. A deep learning algorithm has been proposed to forecast the Korean Stock Price Index (KOSPI) [57], which is believed to help investors view the market better and help firms learn more about their customers via developing better marketing strategies. Using the method called long short-term memory (LSTM) networks, Fisher Tomas has predicted the performance of finance market and formalized a short-term reversal strategy [60].Besides directly forecasting stock price and making portfolios, there also exists some other applications using deep learning in finance. Min-Yuh Day has found some interesting factors that affect the forecasted results. In their research based on deep learning, financial sentiment (such as financial news released on different media) is an important factor which should be considered when forecasting [61].Taking 30 provinces as cases, Chinese energy efficiency and its influence factors have been analyzed, and the accuracy of the best result in deep learning model is higher than 96% [62].

Actually, with the decrease of data storage cost, massive amount of domain-specific information has been collected by different organizations and firms. To get more useful information, deep learning algorithms are becoming increasingly important in such an age of big data [63].

4. Machine learning for business activities

Machine Learning can be roughly categorized into three classes - supervised learning, unsupervised learning and reinforcement learning. The labeled data are used to train in supervised learning, which behaves like a "teacher". On the contrary, unsupervised learning has to find the structure all by itself, which means no labels are given. In reinforcement learning, agent interacts with the environment, learns online and tries to maximize accumulated reward. All those three classes can go on extending into more specified algorithms. From Fig. 4, it can be seen that unsupervised learning contains K-nearest Neighbor, Bayesian Network, Linear Regression, Restricted Boltzmann Machine, Artificial Neural Network, etc. Unsupervised learning contains Clustering, Outlier Detection, etc. And reinforcement learning contains Q-Learning, Recurrent Reinforcement Learning, etc.

Machine learning is a combination of math, finance and computer science. Three more examples are given below. Fig. 5 illustrates logistic regression used in risk control management. Risk control is the core of almost every financial institution. It is fundamentally a classifier. For banks, the purpose of risk control is to distinguish trustworthy people from others. After that they will not be worried about loaning money to them at all. Interpretable models, like logistic regression, decision tree and so on, are well received in the industry. A well-trained logistic regression can separate two kinds of customers (good or bad) steadily. Nearly all credit scorecards are implemented by logistic regression because of its robustness and good explanation of problems.

Fig. 6 illustrates recurrent neural network which used in stock prediction. Stock prediction can be roughly classified into three types according to the prediction target. Predicting prices is one of the hardest problems. Predicting the trends which foresees whether the stock price goes up or down can be much easier, while predicting fluctuation may generate the most reliable results compared with the other two. As raw stock price data changes over time, it's a kind of time-series data. Recurrent neural network is better than other algorithms facing time-series data (stock price), which is a powerful type of neural network developed to deal with sequence dependence. And recurrent neural network is good at solving such problems owing to the connections between units.

Fig. 7 illustrates the decision tree used in decision analysis. Decision tree is a major tool of investment analysis and is often used to decompose complex problems during decision making process and make rational choice. The decision tree here is a little bit different from decision trees used in machine learning nowadays. In the field of machine learning, decision trees are always used as a classifier. The decision tree in Fig. 7 presents probabilities to help people make right choices, which is an application in the area of decision theory.

Machine learning has made great contributions to the development of artificial intelligence during the last fifty years. Much more progress has been made in the latest decade. A huge

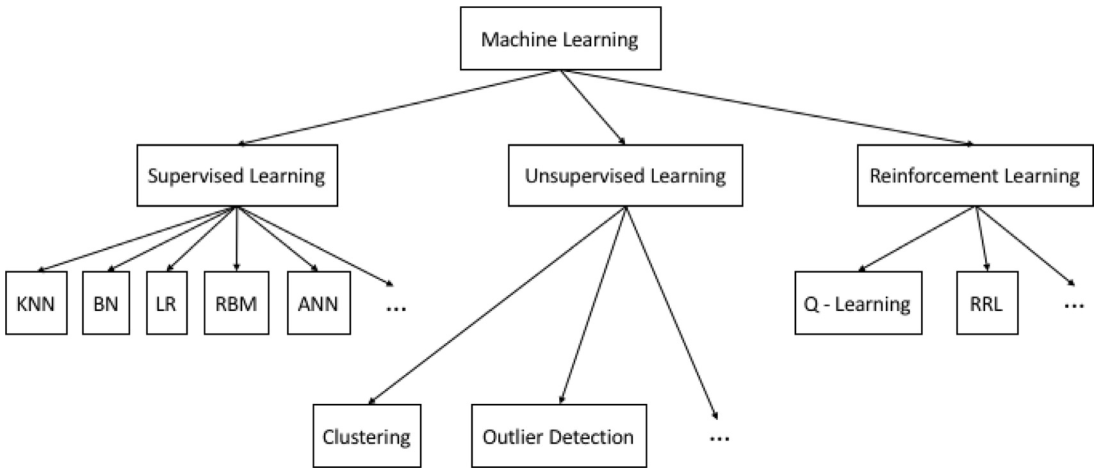

Fig. 4. Graphical representation of machine learning categories.

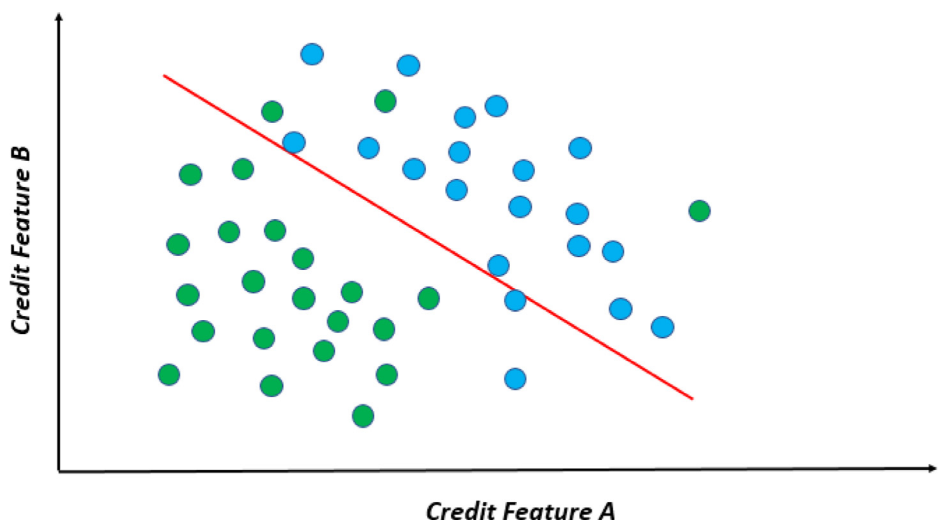

Fig. 5. Illustration of logistic regression used in risk control management.

number of applications of machine learning have come forth in many domains. Recently, scientists from Cornell University designed a quantum machine learning algorithm to solve pattern recognition tasks [64]. Besides, the researchers from Stanford University analyzed enterprise innovation performance dynamically and put forward some strategies and conclusions about knowledge resource [65]. It is believed that finance benefits most from machine learning, especially for the bankruptcy prediction and credit scoring [66]. Song et al. (2014) have assessed the financial statement fraud risk and put forward a hybrid assessment method combining the rule-based system with machine learning [67]. Via the data from Chinese firms, they have optimized the traditional machine learning method and lowered the error rates. Petr Hajek also focuses on financial statement fraud in non-fraudulent firms. It is shown that the Bayesian belief networks (BBN) performs better than other machine learning methods [68]. Not only the firms, but also the consumers' personal credit risk has been studied. Andrew Lo has ever constructed a nonlinear nonparametric forecasting model and reduce the losses of banks in a range from 6% to 25% [69]. Besides bankruptcy prediction and credit scoring, Gerlein et al. (2016) have tried to analyze how to trade profitably by simple machine learning models, and they evaluate machine learning classification in financial trading through many trading simulations [70]. Moreover, the machine learning methods have been extensively used to forecast stock price [71].

Machine learning has also been used in retail industry, manufacturing industry and business administration. For example, Byeonghwa Park has used several machine learning algorithms, such as C4.5, RIPPER, NaïveBayesian, AdaBoos, to analyze house sales. According to the housing data in Fairfax County, Virginia, they proposed an improved housing price prediction model to make better decisions based on more accurate house price valuation [72]. In manufacturing industry, with the help of cluster analysis, supervised machine learning has been used in supervising product state data to improve product quality and firm efficiency. And it also can be used to find the key to solving old or new and problems in manufacturing industry [73, 74]. In the field of firm development and management, Cemil Kuzey has analyzed the connections between firm value and fifteen factors, especially multinationalism. According to the model based on machine learning, a conclusion has been drawn that multinationalism can only determine firm value moderately, which is a bit different from routinizing recognition [75].

The aim of applying machine learning to finance and economics is to make predictions and find patterns. Nowadays, Big Data is one of the key reasons why machine learning is so popular - traditional methods are not enough for exploring, analyzing and leveraging, and machine learning algorithm can outperform economists. Taking stock market prediction as an example, various Machine Learning techniques have been proved to be successful, such as

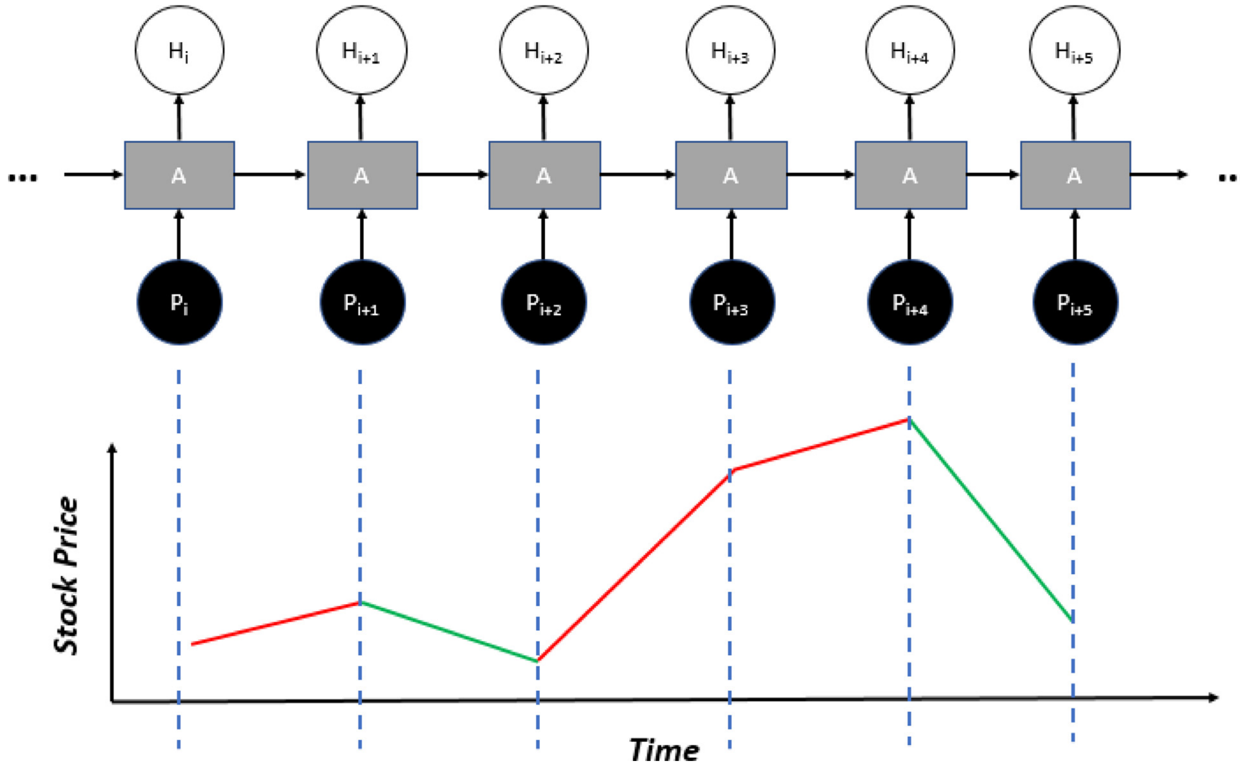

Fig. 6. Illustration of recurrent neural network used in stock prediction.

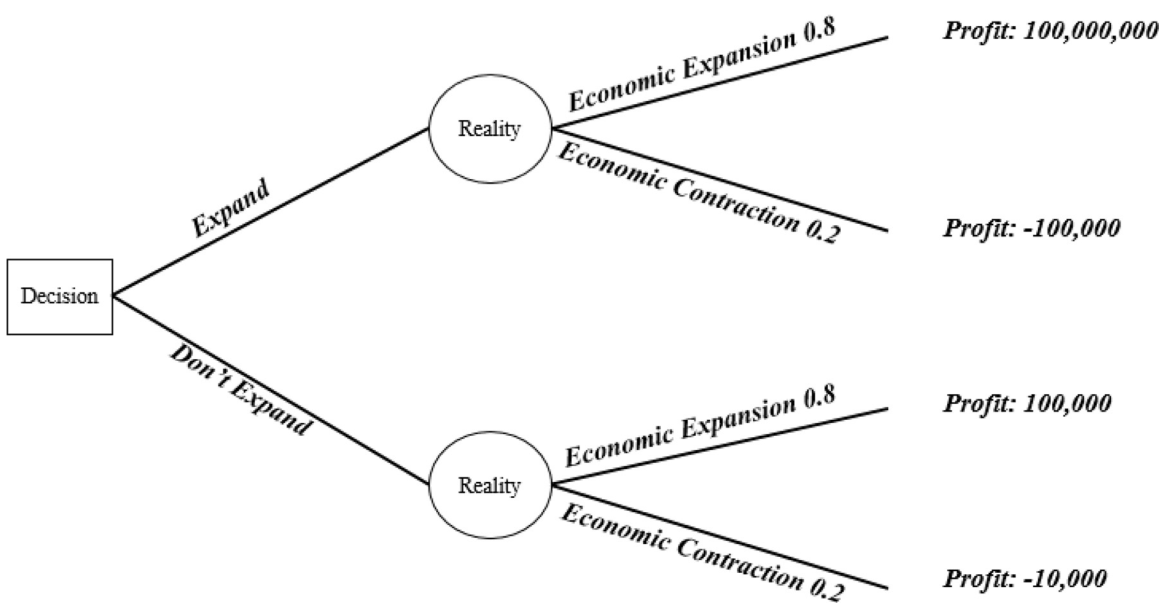

Fig. 7. Illustration of decision tree used in decision analysis.

support vector machine, neural nets and hidden Markov model. Now quantitative analysts ("quants") are one of the hottest topics in Wall Street, as financial securities have become increasingly complex. Another team from Romania has tried to use machine learning and mining data method to discover "hidden" information from data, and help top management in the firm to analysis and make decisions which can better manage customer's relationship [76]. Actually, the cooperation between machine learning techniques and data mining has greatly changed the research status in many domains [77,78].

5. Other technologies: BI (Business intelligence)

Combining with different technologies, business intelligence has become common in enterprise management. Since 1958, when business intelligence was defined by IBM researcher Hans Peter Luhn as "the ability to apprehend the interrelationships of presented facts in such a way as to guide action towards a desired goal", great value of business intelligence has been shown in business activities.

Actually BI had not been widely applied until 1990. Before 1990, only several researchers paid attention to the concept of business intelligence and found out information builders, SAS, PC Focus. The key transition happened in 1990 when Future Gartner Group analyst Howard Dresner redefined business intelligence and expanded its range. Later on, many domains have been greatly influenced by business intelligence, including industry, technology, commercial and future. Since 1990, many firms has put forward their findings and research reports, such as Information Builders, MicroStrategy, QlikTech, RENFE, FedEx and so on.

With the rapid development of business artificial, year 1997 was announced as the start point of "business intelligence" term. After that, more and more famous firms have made contributions to business intelligence, especially in the development of new technology. The launch of Facebook, Twitter, YouTube and the appearance of iPhone and Android have made the progress more distinct. Data shows that the scale and growth rate of business intelligence has become non-negligible. In 2011, a research shows that the top BI trends are cloud computing, big data, predictive analytics, data visualization, search, social networking, and online customer experience.

5.1. Supply chain management

Some researchers, including Matthew A Waller holds the view that the application of DPB (including data science, predictive analytics, big data) will revolute chain design and management [79,80]. Samuel Fosso Wamba adopts the same opinion that big data are probable to revolutionize the art of management and make great impact on operation and strategy [81], when Benjamin T. Hazen pays attention to control data quality with a monitoring method [82]. Actually, in the field of supply chain, there are three major technical challenges, including multi-scale, multi-objective and sustainability, multi-player challenges [83]. To evaluate the influence of different ways based on business intelligence on the challenges above, several models have been proposed, such as maturity framework of SCA (supply chain analytics) [84], interactive visualization system on unexplored area [85], 0–1 multi-objective optimization model [86], sustainable supply chain management model [87], and some other methods have been developed to enhance firm effectiveness and efficiency [88].

Besides creating value, big data and other business intelligence technologies have the potential to transform decision-making processes [89], supporting world-class sustainable manufacturing (WCSM) [90].With the combination of supply chain and business intelligence, the supply chain has been summarized as the demand chain which acquires the firms to operate more effectively [91].

5.2. Business management, including risk management, business performance management, and knowledge management

The business intelligence has been applied in enhancing or optimizing risk management [92–94]. Besides risk management, there are some other researchers paying attention to analyzing business operations [95], increasing systems reliability [96] and business performance management [97–100]. A team from University of Southern Denmark tries to use the NSGA-II algorithm and a model based on adaptive population-based simulated annealing (APBSA) method to ensure the systems reliability. Shuiguang Deng, the leader of the team from University of Zhejiang, has also used the similar model to reduce risk for mobile service composition [101].

Actually, business intelligence has a more crucial effect on enterprise and knowledge management. Based on non-financial methods, Rastislav Rajnoha proposed a new model on strategic and other non-traditional and qualitative indicators [102]. Enhanced with text analysis and based on an OLAP (on-line analytical processing) model, William F. Cody has integrated business intelligence and knowledge management [103].

There are also some new domains benefited from business intelligence. Peng-Yeng Yin has used a method based on enhanced genetic algorithm (EGA) to micro-sit wind farm [104]. With the help of sensitivity analysis, researchers from Taiwan put forward an optimal model to dispatch manpower [105]. Besides these, ERP project [106], real estate industry [107] has also been studied when combined with artificial intelligence by researchers.

Besides, firm profiling is an analytical process to build profound understanding of firm's basic characteristics. It can be seen as an effective way to get crucial information from the specific firm and achieve business intelligence [108].

5.3. Intelligent transportation and sharing economy

Business intelligence can be applied to minimize the time and cost of transportation, with the combination of route optimization, order allocation and price optimization. Route optimization price optimization is about how to find the path from source to destination, which takes the least time and the most reasonable price. Order allocation studies the problem of matching supply with demand considering multidimensional factors such as distance, road conditions, and riding speed. E-commerce like online taxi reservation is also a kind of intelligent transportation.

Another hot topic in the application of business intelligence is sharing economy. It is a kind of business pattern based on temporary exchange of strangers' unused items for profit, which could improve the utilization rate of idle goods and optimize the efficient allocation of the social resources [109]. A variety of transportation mode choices emerge from car-hailing apps, including private-car hailing, taxi hailing, hitch, chauffeur and other intelligent platform service.

As the third highest energy consumption sectors in China and a high GHG emissions sector, Transport sector including urban passenger transportation, faces serious resource and environmental challenges [110,111]. Without controlling the long-term growing trends of vehicle fleet, China's transportation may have some bad impact on CO2 emissions and local air quality, as well as national energy security [112]. Therefore, China is making great effort to promote the rapid and sustainable development of urban transport system, and the transportation sector will play a major role in long-term carbon mitigation [113]. With the help of business intelligence in sharing economy, these problems can be effectively solved. That's why sharing economy blooms so fast in China.

6. Conclusion

In this paper, we present a survey of the artificial intelligence applied in business activities. Discussions mainly emphasize on three aspects – neural networks, deep learning and machine leaning. Then some other technologies such as business intelligence are introduced as supplement.

In recent decades, especially in the 21st century, artificial intelligence which including neural networks, machine learning and deep learning, has made a huge difference for every corner in the world. Large quantities of researches have combined these magic technologies with traditional industries, and they even create a large number of interdisciplinary topics, especially in the field of commercial activities and enterprise management. Artificial intelligence and business intelligence has made great contribution to the development of finance, innovation, entrepreneurship and strategy. To improve the efficiency and performance of business activities, people must make full use of artificial intelligence.

Despite of its prosperity nowadays, artificial intelligence also faces countless challenges. First one is the complexity of artificial intelligence algorithms, as most models of them are seen as "black box", especially discriminative models. This opacity prevents artificial intelligence from being widely used in finance-related area, as people always want to know clearly about the operating process once their money is involved. As Donald Michie stated, "In AI-type learning, explain-ability is all." [114]. Second challenge is how to convert the research results into practical outcomes. Using surveys of research managers, Richard Nelson (1986) found that university research is an important source of innovation in several industries [115]. But a lot of fascinating studies in universities and research institutions are deviated far away from reality.

Another challenge that cannot be neglected is the problem of data. Nowadays the innumerable, redundant and noisy data exists everywhere. There is a tendency that, almost everyone, ranging from big Web firms, traditional firms, to natural scientists or social science researchers, is already experiencing an unparalleled increase in the quantity and quality of data available in their work, which brings new possibilities and huge unexploited value [116]. The first and most important step of using artificial intelligence algorithms is data cleaning. While a lot of low-quality information is available in various data sources and on the Web, many organizations or companies are interested in how to transform the data into cleaned forms which can be used for high-profit purposes [117]. Among all data quality problems, imbalanced data is very common. For instance, in DNA microarray data, class imbalance problem occurs frequently, causing poor prediction performance for minority classes [118]. Although existing knowledge discovery and data engineering techniques have shown great success in many real-world applications, the problem of learning from imbalanced data (the imbalanced learning problem) is a relatively new challenge that has attracted growing attention from both academia and industry. The imbalanced learning problem is concerned with the performance of learning algorithms in the presence of underrepresented data and severe class distribution skews. Due to the inherent complex characteristics of imbalanced data sets, learning from such data requires new understandings, principles, algorithms, and tools to transform vast amounts of raw data efficiently into information and knowledge representation [119]. There exist different methods of solving this problem. The methods are then described and classified in the three categories that have been used in literature: sample methods based on the modification of the training data, kernel methods based on the modification of the kernel and optimization methods based on the modification of the problem formulation [120]. Data quality dominates the result. So how to find proper data and mining what we need is obviously vital and hard.

However, in spite of all those existing challenges, we should believe that there exists more new opportunities for academic research and applications of artificial intelligence in business activities.

7. Future research directions

In the future, there is no doubt that much more domains are going to be affected by artificial intelligence. It's a trend that elites in variety of domains will gradually start to make full use of artificial intelligence. In this section, several directions which are most likely to be the hot topics for the future research will be given.

The very first one is fintech. "Fintech" is an abbreviation of "financial technology," which refers to technology-enabled financial solutions. It has been considered as a close combination of financial services and information technology [121]. Fintech has a huge impact on the finance industry, as artificial intelligence, machine learning, data analytics and Block Chain are all changing the way this industry works. Regarding its potential and effect, it will definitely be one of the hottest research domains in the future.

Rational analysis is the next topic which should be considered. Rational analysis is an empirical program which helps us to explain the aim and function of cognitive processes [122]. Decision theory, which is also called theory of choice, has already been a relatively mature subject. It's the way that helps people analyze the current situation and make rational choices. The developments of artificial intelligence substantially pushed it forward. Compared with human beings, machines and algorithms are much easier to keep calm and "think" thoroughly. Decision making is obviously one of the most important concerns when conducting business activities. In this way, artificial intelligence will assist people to make better decision than before.

Liberating labor is another direct use of artificial intelligence. It can save millions of money for a firm, although it also causes a lot of people lose their job. More repeated and dull work will be finished by "smart" machines, while only the most creative parts are left for human. For example, mechanical arms are used to assemble electronic component instead of workers. To some degrees, labor liberating is the final goal of artificial intelligence. Since ancient times, human beings have been dreaming of artificial intelligence which can be used to explore and exploit tools, so that they can get rid of physical and mental labor [123]. So there's no doubt that it will keep flying high hereafter.

Last but not least, as Andrew Ng, former VP and Chief Scientist of Baidu stated, transfer learning would be an important research direction in the next five years. It's a relatively new concept even in the area of computer science. Transfer learning aims to transfer the knowledge well learned from known domains to improve learning task in a related domain [124]. For instance, in real life the knowledge learned from riding a bicycle will certainly help people in learning how to ride a motorbike. Thus, transfer learning is also believed to be a great opportunity for business activities.

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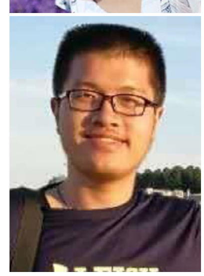

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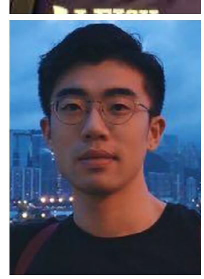

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