On Present Use of Machine Learning based Automation in Finance

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Abstract: In this paper, we survey the current known applications of Machine Learning based Data Analytics and automation in finance industry. We look into the challenges involved in furthering this technology, particularly in employing more Deep Learning approaches proven for successful automation in other domains. We enumerate observations on some of the barriers faced by the industry in effectively adopting and accelerating use of AI techniques, and finally propose more areas that we believe could further benefit from application of Machine Learning.

1 INTRODUCTION

In the recent past, Machine Learning (ML) based data analytics has made significant advances in certain industry sectors e.g. location-based services and US retail (MGI report 2016), however other sectors like manufacturing, the EU public sector, US health care and finance and banking industry are still lagging behind in effectively using ML approaches in solving existing problems or in exploring areas to expand where applying AI may help. As AI techniques are turning into a fundamental component of business growth and remodelling across a wide range of industries, the spectrum of possible applications of AI in these sectors is continuously widening as we gather and organize more and more data for training AI models.

The amount of captured data is roughly doubled every year. According to a 2016 IDC report, by 2025 we would have created 180 Zettabytes of data. Still, at present the progress in capturing value from these data has been uneven across the industries due to many reasons; some of which have been identified as lack of analytical talent, siloed data amongst different companies or groups within a company and scepticism within leaderships with regards to the impact.

In particular, the financial domain is fast catching up in its attempt to utilize AI methods in data analytics-based automation (Kolanovic et al., 2017). The Wall Street looks keen on investing hugely in this area of technology; but there still remains a dearth of technological discussions and literature on identifying areas where e.g., trading strategies, market prediction or correction, risk calculations, pricing models and portfolio management, can leverage from Machine Learning. At best, the financial firms are forging into AI usage in silos thereby creating an even greater need for debate on the future implications of AI usage across this domain.

In this paper, we study the current known applications of AI in finance and banking industry and survey the literature available on Deep Learning approaches both proposed and demonstrated in finance applications. We discuss the known as well as emerging barriers to using AI in this industry and conclude with proposals for further application areas that we believe could benefit from this branch of Machine Learning.

We start with a brief definition of Deep Learning and its related terms and go onto exploring some of the known present applications of Deep Learning in financial sector, discuss some hurdles to ML application in finance and then move on to proposals for additional areas of usage.

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2 DEEP LEARNING

Deep Learning is a branch of Machine Learning that aims at discovering a mapping function between given input data sets and expected output(s). A Deep Learning module would analyse data in multiple steps or *layers* of learning, which means it will begin by learning a few simple concepts and proceed to learning more complex ones by combining the simpler ones in an iterative fashion in these layers.

A generally well-known goal of Artificial Intelligence is to automate human tasks that would be simple and easy for a machine to learn and perform. Deep Learning is different from such automation in that it works on more abstractly defined problems where the learning is attempted by the machine based on data sets on both input and expected output. So far, a prominently used method in Deep Learning is use of Neural Networks which mimic how neurons perform learning in a human brain.

Unlike other Machine Learning techniques, Deep Learning does not involve automating human tasks that are easy to define and perform. Deep Learning aims to discover a mapping function between large and variously sourced input and output datasets thereby eventually developing an 'intuition' to arrive at an accurate output prediction given an input dataset.

2.1 Definitions

A generic Deep Learning module can be described as follows. If there are n layers of Neurons in the Deep Neural Network, let $f1\ldots fn$ be given *univariate activation functions* for each of the n layers.

These *activation functions* are nonlinear transformations of weighted data. The quality of a good predictor depends on the selection of univariate activation functions $f(i)$ at each layer of the neural network. The algorithm extracts hidden factors or features at each layer. Since the weights are matrices, a deep learning predictor has greater flexibility to uncover nonlinear features of the data.

Most commonly we divide the data sets into three subsets, for training, validation, and testing. The training set is used to adjust the weights of the network. The validation set is used to minimize the over-fitting and pertains to model selection. Testing data set is used to confirm the actual predictive power of a deep learner (Heaton et al., 2016).

2.2 Types of Deep Neural Networks

Deep neural networks (DNNs) are more sophisticated artificial neural networks (ANNs) that use several hidden layers. DNNs have proven very successful in retail commerce sector with the use in speech transcription and image recognition (Krizhevsky et al., 2012) due to their superior predictive properties and robustness to overfitting.

The most popular ways Deep Neural Networks can be implemented are as follows:

- Multi-Layer Perceptrons or Feed Forward Networks
- Restricted Boltzmann Networks
- Convolutional Neural Networks
- Long Short-Term Memory

2.2.1 Multi-Layer Perceptron (MLP)

As one of the first designs of multi-layer neural networks, Perceptron is implemented in a Feed Forward way such that the input passes through each node of the neural network exactly once.

2.2.2 Restricted Boltzmann Networks (RBN)

RBNs are based on dimensionality reduction such that the neurons in an RBN form two layers. The first being the visible units (returns of assets) and the second hidden units (hidden factors or features). Neurons within the same type of layer hidden or visible are not connected to each other creating a restriction in the neural network.

2.2.3 Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) are popularly used for classifying and detecting objects in images. A CNN extracts data features by using multiple filters on overlapping segments of the image, deriving first the simple parts and then connected features of an image.

2.2.4 Long Short-Term Memory (LSTM)

Unlike Multi-Layer Perceptron which can only feed forward, Long Short-term memory (LSTM) is a neural network that includes feedback loops between its elements.

LSTM networks work well with time series analysis, as they can recognize patterns across different time scales.

3 DEEP LEARNING USE CASES IN FINANCE

3.1 Portfolio Selection and Pricing

Although most Hedge Funds keep their portfolio pricing methodologies strictly confidential, it's been demonstrated by a few that using Machine Learning to price portfolios in overly aggressive markets, firms can discover hidden features in their portfolio data and adjust pricing to maximize profit.

(Heaton et al., 2016) Worked on finding a selection of investments for which good out-of-sample tracking properties of their objective could be discovered. They used weekly returns data for the component stocks of the biotechnology IBB index for a period of about four years and trained a deep learner without knowledge of the component weights.

By implementing a four-step Deep Learning algorithm which goes from auto-encoding, calibrating, validating, to verifying they show that a data-driven and model-independent Deep Learning approach can be a new paradigm for prediction.

3.2 Financial Markets Predictions

Due to the computation complexities involved in using Deep Neural Networks (DNNs) in algorithmic trading, their proposed usage has posed a few concerns. The financial research communities and practitioners are still to find a meeting ground where the traditional financial econometrics joins hands with practical machine learning.

In their research (Dixon et al., 2016), use DNNs to model complex non-linear relationships between the independent variables and dependent variable with reduced tendency to over-fit. To do so they utilize low cost multi-core accelerator platform to train and tune the parameters of their model. They exploit state-of-the-art parallel computing architecture to implement a feed-forward topology for multivariate forecasting analysis. Using 5 minute interval prices over five years, they simultaneously train a single model from a large number of signals across multiple instruments instead of one model for each instrument. The aggregated model is thus able to capture a more complete set of information to describe time-varying movements for each instrument's price. They claim that their model is able to predict the direction of instrument movement to average 42% accuracy with a standard dev of 11% across the instruments. The parallel trained model also yields back testing accuracy which directly translates into P&L for simple long-only trading strategy.

3.3 Bond and Options Pricing

Bond markets suffer from a comparative lack of trading information as opposed to equity trading. Many bond prices are days old and do not represent latest market developments due to the fact that the information available on bond trades is scarcely available often on a fee for data contract basis (Benchmark Solutions, 2014).

(Ganguli et al., 2017) Show in their experiments that Neural Networks give very accurate results without overfitting in reasonable amounts of time (order of hours). The success of Neural Networks on this dataset implies that investigating the application of multilayer networks and Deep Learning methods to this problem may yield better bond price predictions.

(Deoda et al., 2011) investigated option pricing performance of non-parametric machine learning techniques for Nifty index call options versus parametric Black-Scholes model for 1-day & 1-week price forecast. Their results suggest non-parametric machine learning techniques outperform parametric Black-Scholes model. They observed that the nonparametric machine learning techniques adjust more rapidly to changing market behavior and are able to capture the pattern more effectively compared to parametric models.

Using more sophisticated techniques such as Deep Learning for calibrating the models and filtering the data, pricing performance can be improved even further.

3.4 Stock Pricing based on Sentiment Analysis

The stock market is influenced by various factors including a plethora of human-related ones some of which can be regime change, political scenarios, climate, news media etc. Financial predictive analytics can benefit from Deep Learning by using most such factors to train the analytical models and predict trends and signals.

In their research (Ding et al., 2015) demonstrate that Deep Learning is useful for event-driven stock price movement prediction. They propose a novel Neural Tensor Network for learning *event embedding*, and use a Deep Convolutional Neural Network (CNN) to model the combined influence of long-term events and short-term events on stock price movements. Their results show that event embedding-based representations perform better than discrete events-based methods, and deep CNN capture longer-term influence of news event than standard feed-forward neural network. They use a simple greedy strategy to simulate the market to make their model yield relatively more profit.

3.5 Real-time Fraud Detection and Compliance

Machine Learning algorithms have been in use in the area of detecting credit card fraud for some time now. However the presently used ML techniques are still rule-based and individual transaction oriented. Fraud monitoring systems today are not able to detect complex transactional patterns resulting into a huge amount of false positive fraud alerts which require human assessment and filtering.

There are nonetheless, huge credit card transactions datasets available with the providers that can be used to train systems that not only detect but also predict fraudulent transactions.

Deep Learning has the potential to improve detection of fraudulent and money laundering activities. Deep Neural Networks have been shown to identify complex patterns in the data and combine transactions information at network speed, utilizing data from many different sources to yield a more complete picture of a client's activity. These systems have been shown to bring false positives down significantly as well.

3.6 Statistical vs. Deep Learning Models

According to a report, more financial institutions are now replacing their older statistical-modelling algorithms with machine learning techniques. These institutions have reportedly observed 10 percent increases in sales of new products, 20 percent savings in capital expenditures, 20 percent increases in cash collections, and 20 percent declines in churn. Deep Learning can help banks implement more outreaching and effective recommendation engines for clients in retailing and in small and medium-sized companies. These systems can employ micro-targeted models that more accurately forecast who will cancel service or default on their loans, and how best to intervene (Lalithraj et al., 2017).

4 BIASES AND BARRIERS

4.1 Biases

As we survey the use of Machine Learning based analytics of big data in finance, we cannot ignore the ubiquity of biases in learning from the data. Bias is present in every type of learning. Bias in learning is defined as *any basis for choosing one generalization over another, other than strict consistency with the instances* (Mitchell, 1980). Categorizing originally as only two broad ways as *representational* and *procedural* (Gordon et al., 1995) suggest that selection and evaluation of biases is critical task for any intelligent systems. These biases in the present Machine Learning based analytic applications can be further specified as algorithm bias and data bias which further subdivides into Sample, Prejudicial, and Measurement Biases on Data. Creating standards and frameworks to allow a balance of biases and variance in training data for financial applications is a task impending on the regulatory bodies and consortiums.

In addition to biases, there are multiple barriers that the industry faces in application of AI to its fullest potential. Some of which are discussed briefly here.

4.2 Data Confinement

A firm's data is its competitive advantage over others. In some instances, the analytical value derived from this data allows the firm to disrupt the industry by strengthening its core business while in others whole new business models can be adopted as a result of learning from the data at its disposal. However, *data confinement* is a prominent issue facing many of the finance and banking industry. Additionally, as opposed to consumer applications, finance and banking industry have less data to individualize their services beyond their present consumers. *Transfer Learning* is proposed as a more promising technique than Deep Learning in such cases where labelled training data from a related domain can be used in further learning from outside data.

4.3 Disparate Data Formats

Another practical reality about data present in finance and banking industry is the multitudes of data formats like PDFs, MS Word documents, Excel Sheets, to name a few. Deriving interchangeable information from these formats becomes a challenge for AI methods like Natural Language Processing (Carlton et al., 2017).

Cleaning and consolidating gathered data for training, from different data sources within a firm is also an organizational challenge faced in creating useful AI based applications as data often sits in silos amongst different groups across the firm.

4.4 Interpretability and Model Locality

The fierce competition to apply machine learning in finance has been motivating data scientists to experiment with complex predictive modelling using for example artificial neural networks (ANN) and gradient boosted ensembles (GBM). While this is being done with a goal to achieve more predictive accuracy, the models are increasingly becoming black-boxes due to their unexplainable inner workings.

Model interpretability is critical for documentation and regulatory oversight, business and human adoption. Finance and banking industry face stricter regulatory and documentation requirements, forcing financial data scientists to continue to use traditional linear modelling to create their predictive models.

Additionally, as finance and banking industry adopt more machine learning based automation into their decision-making systems, interpretability becomes ever more important for ruling out any deliberate or prejudicial decisions (Patrick et al., 2017).

It is well known that learning algorithms can produce multiple accurate models with very similar internal architectures (Chiyuan et al., 2017), provided the same input dataset and targets. This phenomenon is known as *model locality* and is another hurdle to model interpretation.

Various testing techniques like *model visualization*, *reason code generation*, and *sensitivity analyses* have been proposed to ensure interpretability, however this area demands more practicable research and tools development and eventually industry wide standardization and adoption.

The area of testing predictive models for interpretability, fairness, accountability and trustworthiness (FAT) is fast evolving, however it has proven to be more intricate to apply in finance industry.

5 PROPOSED AREAS OF USAGE FOR DEEP LEARNING

5.1 Pricing and Risk Calculations

Financial risk management today relies on acquiring and using several sources of data to run sophisticated algorithms to compute results in advance (Liebergen, 2017).

Deep Learning has proven ability to analyse very large amounts of data from multiple sources and can be used to produce in-depth predictive analysis with high granularity (Härle, et al., 2016), thereby holding the potential to greatly enhance analytics in risk management as well as compliance.

There are also emerging systems where User Defined Functions enable analytics at the data level within the infrastructure. (Kinetica., 2017) is one such example. UDFs enable a next generation risk management platform that will also allow real-time drill-down analytics and on-demand custom XVA library execution.

5.2 Financial Time Series Forecasting

One of the important components of financial time series forecasting is stock index prediction. Derivative trading vehicles based on stock indices provide the means to hedge against systemic risks and diversify a portfolio. Finding better techniques for stock index prediction is a continuous challenge as it equips the market participants to make better investment decisions.

(Krollner et al., 2010) observe that Artificial Neural Networks (ANNs) have been identified as the dominant machine learning technique in this area. However, while the market researchers agree on the importance of stock index forecasting, the task of experimenting with deep neural networks is yet to be done.

5.3 Technical Analysis

As mentioned earlier, Convolutional Neural Networks have proven to be very efficient in classifying images and object detection.

There are proposals to use CNN in the trading, in particular in the area of technical analysis to detect price chart patterns of technical analysts which are difficult to define mathematically. As technical analyses can have many variations based on time scale.

(Krizhevsky et al., 2012) propose that various technical patterns and even specific calls from prominent technical analysts can be used to train CNNs, and then tested for their predictive power is in the specific pattern, or specific analyst. Patterns with significant forecasting power can be automated and applied over a broad range of assets at a scale that would be impossible to achieve by a human technical analyst.

5.4 Audit and Reporting

Audit and Reporting processes involve massive amounts of data and require auditors to solve, such as text analysis, speech recognition, and parsing images and videos.

Deep learning can help by automating the routine tasks to improve audit efficiency and effectiveness by facilitating repetitive audit procedures and supporting audit judgments. Automating some substantive procedures, such as confirmation and examination will allow auditors to perform tasks that are currently cost prohibitive or too complex, for example exhaustively examining all corporate contracts.

6 CONCLUSIONS

Machine Learning has proven to be an effective framework in the areas of speech and image recognition. It offers a system to use large data sets to learn abstract mathematical definitions.

Financial industry continues to utilize statistical models to make decisions like portfolio selection, stock market prediction, risk calculations, pricing models etc. Machine learning has the potential to improve on predictive performance in financial applications. However, there are many known obstacles to adopting AI in finance in the current state of affairs.

Inherent data and model biases underlying the machine learning based automation have created an ever-increasing need for regulatory oversight and hence force financial data scientists to continue to rely on their traditional linear predictive models.

While non-linear models created by trained machine learning algorithms may produce more accurate predictions resulting into better financial margins, the approvability of such models still remains in the hands of business partners, and regulators.

Explainable AI and Machine Learning interpretability are areas of research that are subject to rapid changes and expansions at the moment. Interpretable Machine Learning models are still very difficult to achieve and hence finance and banking industry have to start focusing more on explainable models and their interpretability before any real applications of ML.

In this paper we surveyed several areas in financial data science where Machine Learning is either presently being used or has been demonstrated beneficial to use through research. We considered some of the biases and barriers in the application of Machine Learning in financial domain. In the end, discussed several other areas in financial domain where Deep Learning can be utilized effectively.

Areas that require further work both in terms of research and in tools and processes development include but are not limited to bias selection and model interpretability. Among other hurdles to using AI in finance are, rethinking solutions to data confinement and utilizing disparate data hosted by financial firms for training Machine Learning models.

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