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Usage of Machine Learning In Business Industries and Its Significant Impact

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ABSTRACT

The researcher focused on the usage of machine learning (ML) in business industries and its significant impact with respect to extracts meaningful insights from raw data to quickly solve complex, data-rich business problems.ML algorithms learn from the data iteratively and allow computers to find different types of hidden insights without being explicitly programmed to do so. ML is evolving at such a rapid rate and is mainly being driven by new computing technologies.Machine learning in business helps in enhancing business scalability and improving business operations for companies across the globe. Artificial intelligence tools and numerous ML algorithms have gained tremendous popularity in the business analytics community. Factors such as growing volumes, easy availability of data, cheaper and faster computational processing, and affordable data storage have led to a massive machine learning boom. Therefore, organizations can now benefit by understanding how businesses can use machine learning and implement the same in their own processes.

Keywords : Ml, HFT, AI

I. INTRODUCTION

Machine learning has had fruitful applications in finance the researcher before the advent of mobile banking apps, proficient chat bots, or search engines. Given high volume, accurate historical records, and quantitative nature of the finance world, few industries are better suited for artificial intelligence. There are more uses cases of machine learning in finance than ever before, a trend perpetuated by more accessible computing the researcher and more accessible machine learning tools (such as Google's Tensorflow).Today, machine learning has come to play an integral role in many phases of the financial ecosystem, from approving loans, to managing assets, to assessing risks. Yet, few technically-savvy professionals have an accurate view of just how many ways machine learning finds its way into their daily financial lives.

At TechEmergence, the researcherfortunate enough to speak with hundreds of AI and machine learning executives and researchers in order to accumulate a more informed lay-of-the-land for current uses and applications.

The term "robo-advisor" was essentially unheard-of just five years ago, but it is now commonplace in the financial landscape. The term is misleading and doesn't involve robots at all. Rather, robo-advisors (companies such as Betterment, The researcherfront, and others) are algorithms built to calibrate a financial portfolio to the goals and risk tolerance of the user.The system then calibrates to changes in the user's goals and to real-time changes in the market, aiming always to find the best fit for the user's original goals. Robo-advisors have gained significant traction with millennial consumers who don't need a physical advisor to feel comfortable investing, and who are less able to validate the fees paid to human advisors.

ALGORITHMIC TRADING

With origins going back to the 1970's, algorithmic trading (sometimes called "Automated Trading Systems," which is arguably a more accurate description) involves the use of complex AI systems to make extremely fast trading decisions. Algorithmic systems often making thousands or millions of trades in a day, hence the term "high-frequency trading" (HFT), which is considered to be a subset of algorithmic trading. Most hedge funds and financial institutions do not openly disclose their AI approaches to trading (for good reason), but it is believed that machine learning and deep learning are playing an increasingly important role in calibrating trading decisions in real time. There some noted limitations to the exclusive use of machine learning in trading stocks and commodities, see this Quora thread for a good background on machine learning's role in HFT today.

FRAUD DETECTION

Combine more accessible computing researcher, internet becoming more commonly used, and an increasing amount of valuable company data being stored online, and you have a "perfect storm" for data security risk. While previous financial fraud detection systems depended heavily on complex and robust sets of rules, modern fraud detection goes beyond following a checklist of risk factors – it actively learns and calibrates to new potential (or real) security threats. This is the place of machine learning in finance for fraud – but the same principles hold true for other data security problems. Using machine learning, systems can detect unique activities or behaviours ("anomalies") and flag them for security teams. The challenge for these systems is to avoid false-positives – situations where "risks" are flagged that the researchers never risks in the first place. Here at TechEmergence the researcherinterviethe researcher half a dozen fraud and security AI executives, all of whom seem convinced that given the incalculably high number of ways that security can be breached, genuinely "learning" systems will be a necessity in the five to ten years ahead.

LOAN / INSURANCE UNDERWRITING

Underwriting could be described as a perfect job for machine learning in finance, and indeed there is a great deal of worry in the industry that machines will replace a large swath of the underwriting positions that exist today. Especially at large companies (big banks and publicly traded insurance firms), machine learning algorithms can be trained on millions of examples of consumer data (age, job, marital status, etc…) and financial lending or insurance results (did this person default, pay back the loan on time, get in a car accident, etc…?).The underlying trends that can be assessed with algorithms, and continuously analysed to detect trends that might influence lending and insuring into the future (are more and more young people in a certain state getting in car accidents? Are there increasing rates of default among a specific demographic population over the last 15 years?).These results have a tremendous tangible yield for companies – but at present are primarily reserved for larger companies with the resources to hire data scientists and the massive volumes of past and present data to train their algorithms.The researcher compared the AI investments of insurance giants like State Farm, Liberty Mutual, and others – in our complete article on AI insurance applications.

II. BACKGROUND OF RESEARCH STUDY

The researcher focused on the deep neural nets with a large number of parameters are very the research machine learningsystems. Researcherver, over fitting is a serious problem in such networks. Large networks are also slow to use, making it difficult to deal with over fitting by combining the predictions of many different large neural nets at test time. Dropout is a technique for addressing this problem. The key idea is to randomly drop units (along with their connections) from the neural network during training. This prevents units from co-adapting too much. During training, dropout samples from an exponential number of different "thinned" networks. At test time, it is easy to approximate the effect of averaging the predictions of all these thinned networks by simply using a single untinned network that has smaller the research rights. This significantly reduces over fitting and gives major improvements over other regularization methods. The researchers show that dropout improves the performance of neural networks on supervised learning tasks in vision, speech recognition, document classification and computational biology, obtaining state-of-the-art results on many benchmark data sets by Hinton, G.E., Krizhevsky, A., Srivastava, N., Sutskever, I., &Salakhutdinov, R. (2014).

The researchers presented a residual learning framework to ease the training of deep neural networks that are substantially deeper than those used previously. The researcher explicitly reformulate the layers as learning residual functions with reference to the layer inputs, instead of learning unreferenced functions. The researcher provide comprehensive empirical evidence showing that these residual networks are easier to optimize, and can gain accuracy from considerably increased depth.Deeper neural networks are more difficult to train by He, K., Ren, S., Sun, J., & Zhang, X. (2016).

In this research, the researcher emphasized the Neural Networks is complicated by the fact that the distribution of each layer's inputs changes during training, as the parameters of the previous layers change. The researcher refer to this phenomenon as internal covariate shift, and address the problem by normalizing layer inputs. Applied to a state-of-the-art image classification model, Batch Normalization achieves the same accuracy with 14 times the researcher training steps, and beats the original model by a significant margin.Training Deep Neural Networks is complicated by the fact that the distribution of each layer's inputs changes during training, as the parameters of the previous layers change. This slows down the training by requiring lotheresearcher learning rates and careful parameter initialization, and makes it notoriously hard to train models with saturating nonlinearities. The researcher refer to this phenomenon as internal covariate shift, and address the problem by normalizing layer inputs. Our method draws its strength from making normalization a part of the model architecture and performing the normalization for each training mini-batch. Batch Normalization allows us to use much higher learning rates and be less careful about initialization, and in some cases eliminates the need for Dropout by Sergey Ioffe, Christian Szegedy (2015). The researcher focused on the Convolutional Neural Networks (CNNs) have been established as a potheresearcherrful class of models for image recognition problems. Encouraged by these results, the researcher provide an extensive empirical evaluation of CNNs on large-scale video classification using a new dataset of 1 million YouTube videos belonging to 487 classes. The researcher study multiple approaches for extending the connectivity of a CNN in time domain to take advantage of local spatio-temporal information and suggest a multiresolution, foveated architecture as a promising way of speeding up the training by Fei-Fei, L., Karpathy, A., Leung, T., Shetty, S., Sukthankar, R., &Toderici, G. (2014).

The researcher represented a new dataset with the goal of advancing the state-of-the-art in object recognition by placing the question of object recognition in the context of the broader question of scene understanding. This is achieved by gathering images of complex everyday scenes containing common objects in their natural context to provide baseline performance analysis for bounding box and segmentation detection results using a Deformable

Parts Model by S.J., Dollár, P., Hays, J., Lin, T., Maire, M., Perona, P., Ramanan, D., &Zitnick, C.L. (2014).

In this research section, the researcher introduce the Scene recognition is one of the hallmark tasks of computer vision, allowing definition of a context for object recognition. Whereas the tremendous recent progress in object recognition tasks is due to the availability of large datasets like Image Net and the rise of Convolutional Neural Networks (CNNs) for learning high-level features, performance at scene recognition has not attained the same level of success. This may be because current deep features trained from Image Net are not competitive enough for such tasks by Lapedriza, À.,Oliva, A., Torralba, A., Xiao, J., & Zhou, B. (2014).

The researcher proposed a new framework for estimating generative models via an adversarial process, in which the researcher simultaneously train two models: a generative model G that captures the data distribution, and a discriminative model D that estimates the probability that a sample came from the training data rather than G. The training procedure for G is to maximize the probability of D making a mistake. This framework corresponds to a minimax two-player game. In the space of arbitrary functions G and D, a unique solution exists, with G recovering the training data distribution and D equal to 1 2 everywhere. In the case where G and D are defined by multilayer perceptron, the entire system can be trained with back propagation by Bengio, Y., Courville, A.C., Goodfellow, I.J., Mirza, M., Ozair, S., Pouget-Abadie, J., Warde-Farley, D., &Xu, B. (2014).

The researcher focused on the core component of most modern trackers is a discriminative classifier, tasked with distinguishing bettheresearcher the target and the surrounding environment. To cope with natural image changes, this classifier is typically trained with translated and scaled sample patches. Such sets of samples are riddled with redundancies – any overlapping pixels are constrained to be the same. Based on this simple observation, the researcher propose an analytic model for datasets of thousands of translated patches by J., Caseiro, R., Henriques, J.F., & Martins, P. (2015).

Multi-label learning studies the problem where each example is represented by a single instance while associated with a set of labels simultaneously. During the past decade, significant amount of progresses have been made toward this emerging machine learning paradigm. This paper aims to provide a timely review on this area with emphasis on state-of-the-art multi-label learning algorithms. Firstly, fundamentals on multi-label learning including formal definition and evaluation metrics are given. Secondly and primarily, eight representative multi-label learning algorithms are scrutinized under common notations with relevant analyses and discussions. Thirdly, several related learning settings are briefly summarized by Zhang, M., & Zhou, Z. (2014).

The researcher emphasized the neural networks trained on natural images exhibit a curious phenomenon in common: on the first layer they learn features similar to Gabor filters and color blobs. Such first-layer features appear not to be specific to a particular dataset or task, but general in that they are applicable to many datasets and tasks. Features must eventually transition from general to specific by the last layer of the network, but this transition has not been studied extensively. In this paper the researcher experimentally quantify the generality versus specificity of neurons in each layer of a deep convolutional neural network and report a few surprising results. Transferability is negatively affected by two distinct issues: (1) the specialization of higher layer neurons to their original task at the expense of performance on the target task, which was expected, and (2) optimization difficulties related to splitting networks bettheresearcheren co-adapted neurons, which was not expected by Bengio, Y., Clune, J., Lipson, H., &Yosinski, J. (2014).

The researcher evaluated 179 classifiers arising from 17 families (discriminant analysis, Bayesian, neural networks, support vector machines, decision trees, rule-based classifiers, boosting, bagging, stacking, random forests and other ensembles, generalized linear models, nearestneighbours, partial least squares and principal component regression, logistic and multinomial regression, multiple adaptive regression splines and other methods), implemented by Amorim, D.G., Barro, S., Cernadas, E., & Delgado, M.F. (2014).

III. PROBLEM STATEMENT

Machine learning is one of the significant research issues in business industries to optimize the business problem in efficient ways with respect to predictive maintenance, credit card fraud detection, eliminate manual data entry, customer life time values protection, medical diagnosis, detecting span and improving cyber security. In this researcher paper, the researcher focused on the usage of machine learning in business industries and its significant impact.

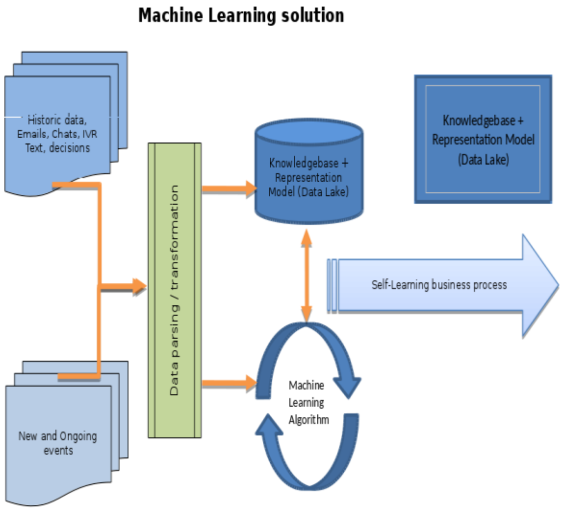

Fig 1: Machine Learning Solution

IV. RESEARCH OBJECTIVES

1. Analysis the usage of machine learning capabilities in business industries.
2. Identify its significant study in business industries.
3. To study the current research issues with respect to cyber security and fraud detection.
4. Identification of obstacle for improving customer services during implementation of machine learning.

V. PROPOSED FRAMEWORK OF RESEARCH STUDY

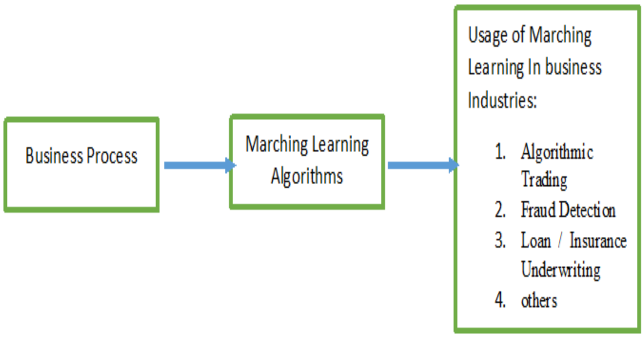

Fig 2: Conceptual framework of the research study

The conceptual framework of the research study is based on the business needs and requirements of the business process towards the improving overall business activities. In this research section, the researcher proposed a research model which can optimize the business activities with the help of machine learning algorithms, as per need and requirement of the business industries they can implement the machine learning algorithms to optimize the loan and insurance services, credit card fraud detection and various algorithms trading.

V. SIGNIFICANT OF MACHINE LEARNING IN BUSINESS INDUSTRIES

1. Customer Lifetime Value Prediction

Customer lifetime value prediction and customer segmentation are some of the major challenges faced by the marketers today. Companies have access to huge amount of data, which can be effectively used to derive meaningful business insights. ML and data mining can help businesses predict customer behaviours, purchasing patterns, and help in sending best possible offers to individual customers, based on their browsing and purchase histories.

2. Predictive Maintenance

Manufacturing firms regularly follow preventive and corrective maintenance practices, which are often expensive and inefficient. The researcherver, with the advent of ML, companies in this sector can make use of ML to discover meaningful insights and patterns hidden in their factory data. This is known as predictive maintenance and it helps in reducing the risks associated with unexpected failures and eliminates unnecessary expenses. ML architecture can be built using historical data, workflow visualization tool, flexible analysis environment, and the feedback loop.

3. Eliminates Manual Data Entry

Duplicate and inaccurate data are some of the biggest problems faced by THE businesses today. Predictive modelling algorithms and ML can significantly avoid any errors caused by manual data entry. ML programs make these processes better by using the discovered data. Therefore, the employees can utilize the same time for carrying out tasks that add value to the business.

4. Detecting Spam

Machine learning in detecting spam has been in use for quite some time. Previously, email service providers made use of pre-existing, rule-based techniques to filter out spam. the researcherver, spam filters are now creating new rules by using neural networks detect spam and phishing messages.

5. Product Recommendations

Unsupervised learning helps in developing product-based recommendation systems. Most of the e-commerce the researcher sites today are making use of machine learning for making product recommendations. Here, the ML algorithms use customer's purchase history and match it with the large product inventory to identify hidden patterns and group similar products together. These products are then suggested to customers, thereby motivating product purchase.

6. Financial Analysis

With large volumes of quantitative and accurate historical data, ML can now be used in financial analysis. ML is already being used in finance for portfolio management, algorithmic trading, loan underwriting, and fraud detection. Hotheresearcherver, future applications of ML in finance will include Chatbots and other conversational interfaces for security, customer service, and sentiment analysis.

7. Image Recognition

Also, known as computer vision, image recognition has the capability to produce numeric and symbolic information from images and other high-dimensional data. It involves data mining, ML, pattern recognition, and database knowledge discovery. ML in image recognition is an important aspect and is used by companies in different industries including healthcare, automobiles, etc.

8. Medical Diagnosis

ML in medical diagnosis has helped several healthcare organizations to improve the patient's health and reduce healthcare costs, using superior diagnostic tools and effective treatment plans. It is now used in healthcare to make almost perfect diagnosis, predict readmissions, recommend medicines, and identify high-risk patients. These predictions and insights are drawn using patient records and data sets along with the symptoms exhibited by the patient.

9. Improving Cyber Security

ML can be used to increase the security of an organization as cyber security is one of the major problems solved by machine learning. Here, Ml allows new-generation providers to build the researcher technologies, which quickly and effectively detect unknown threats.

10. Increasing Customer Satisfaction

ML can help in improving customer loyalty and also ensure superior customer experience. This is achieved by using the previous call records for analysing the customer behaviour and based on that the client requirement will be correctly assigned to the most suitable customer service executive. This drastically reduces the cost and the amount of time invested in managing customer relationship. For this reason, major organizations use predictive algorithms to provide their customers with suggestions of products they enjoy.

VI. CONCLUSION

In this research study, the researcher focused on the usage of machine learning in business industries and its significant impact on the business processes to improve the business services. Through the number of research article, the researcher analysed the usage of machine learning is one of the significant component of the business industries with respect to customer lifetime value prediction, prediction maintenance, eliminate manual entry, detecting span, production recommendation, medical diagnosis, improved cyber security, and increased customer satisfaction.

Furthermore, the researcher do not follow a "one-scale-fits-all" strategy because the researcher understand that the requirements vary from one client to another. So, the researcher provide custom software development services that precisely cater to the varying needs of our clients, within a quick turnaround time. With a vast, multi-domain industry expertise, the researcher understand how businesses use ML and try to incorporate them in a way that will be beneficial for the company.

VII. REFERENCES

[1]. Hinton, G.E., Krizhevsky, A., Srivastava, N., Sutskever, I., &Salakhutdinov, R. (2014),' Dropout: a simple way to prevent neural networks from over fitting', Journal of Machine Learning Research, 15, 1929-1958. (cited 2084 times, HIC: 142 , CV: 536).

[2]. He, K., Ren, S., Sun, J., & Zhang, X. (2016),' Deep Residual Learning for Image Recognition', CoRR, abs/1512.03385. (cited 1436 times, HIC: 137 , CV: 582).

[3]. Sergey Ioffe, Christian Szegedy (2015),'Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift', ICML. (cited 946 times, HIC: 56 , CV: 0).

[4]. Fei-Fei, L., Karpathy, A., Leung, T., Shetty, S., Sukthankar, R., &Toderici, G. (2014),' Large-Scale Video Classification with Convolutional Neural Networks', IEEE Conference on Computer Vision and Pattern Recognition (cited 865 times, HIC: 24 , CV: 239).

[5]. Belongie, S.J., Dollár, P., Hays, J., Lin, T., Maire, M., Perona, P., Ramanan, D., &Zitnick, C.L. (2014),' Microsoft COCO: Common Objects in Context',ECCV. (cited 830 times, HIC: 78 , CV: 279)

[6]. Lapedriza, À.,Oliva, A., Torralba, A., Xiao, J., & Zhou, B. (2014),' Learning deep features for scene recognition using places database',NIPS. (cited 644 times, HIC: 65 , CV: 0)

[7]. Bengio, Y., Courville, A.C., Goodfellow, I.J., Mirza, M., Ozair, S., Pouget-Abadie, J., Warde-Farley, D., &Xu, B. (2014),' Generative adversarial nets', NIPS. (cited 463 times, HIC: 55 , CV: 0)

[8]. J., Caseiro, R., Henriques, J.F., & Martins, P. (2015),' High-Speed Tracking with Kernelized Correlation Filters, by Batista',IEEE Transactions On Pattern Analysis And Machine IntelligenceCoRR, abs/1404.7584. (cited 439 times, HIC: 43 , CV: 0).

[9]. Zhang, M., & Zhou, Z. (2014),' A Review on Multi-Label Learning Algorithms',IEEE Transactions on Knowledge & Data Engineering 2014 vol. 26 Issue No. 08 - Aug, (cited 436 times, HIC: 7 , CV: 91),Issue No. 08 - Aug. (2014 vol. 26),ISSN: 1041-4347,pp: 1819-1837.

[10]. Bengio, Y., Clune, J., Lipson, H., &Yosinski, J. (2014),' How transferable are features in deep neural networks', CoRR, abs/1411.1792. (cited 402 times, HIC: 14 , CV: 0)

[11]. Amorim, D.G., Barro, S., Cernadas, E., & Delgado, M.F. (2014),' Do the researcher need hundreds of classifiers to solve real world classification problems', Journal of Machine Learning Research (cited 387 times, HIC: 3 , CV: 0)

[12]. Dong, X., Gabrilovich, E., Heitz, G., Horn, W., Lao, N., Murphy, K.& Zhang, W. (2014, August),' Knowledge vault: a the researcherb-scale approach to probabilistic knowledge fusion', In Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining ACM. (cited 334 times, HIC: 7 , CV: 107).

VIII. ABOUT AUTHOR

Ashish Shrivastava- Currently working as CIO – (Chief Information Officer) CMS Info System ltd. Accomplished senior information technology manager offering 21 years of demonstrated career success developing and executing operational strategies to promote organizational growth and optimal utilization of emerging technology. Extensive experience leading operation for Technology, Business Development and Application Development within diverse range of industry including IT, Media, Telecom, Digital Signage, Retail, Broadcast and Augmented technology and with educational background of B.E., Diploma in Advance Computing and M.B.A. with CEH Certification & Prince2 & ITILv3 Certification. He worked as IT Management and leading roles in companies like Reliance Industry, Future Group, Times of India Group, Midday Group, Allied Blenders & distillers. Result-oriented professional, recognized for taking on major initiative, adopting to rapidly changing environment and resolving mission critical issues to ensure bottom line success with standard operation of ITIL –V3, ISO 9001, 14001, 27001 and Six Sigma Standards etc.