Machine Learning in Business: A Short Overview

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***Abstract*—Machine learning is viewed as one of the most progressive and researched areas in recent years. While many businesses are adopting the technology there is quite a big percentage of organizations that are facing challenges when deciding on their machine learning strategy. This article is an overview of the term "business process" and the ways a machine learning algorithm can be implemented in it. Some challenges when designing and using machine learning algorithms for a real-time business environment are reviewed.**

Keywords—business processes, business, machine learning, challenges, accuracy, interpretability

I. Introduction

Machine learning is viewed as one of the most progressive and researched areas in recent years. With such a broad application area, it is only natural that the business would want to benefit from it. Research on the topic of machine learning is quite a lot and this paper aims to give an overview of some of it. The publication is structured as follows: Section II gives a definition to the term "business process"; Section III outlines some of the challenges when building and implementing a machine learning model for business purposes. Section IV gives some guides when choosing an algorithm for machine learning. Finally, some conclusions are presented.

II. Business Processes

In times where the client expects their every need to be met at the moment of its appearance and the constant emerging of new competitors capable to offer better products or services faster, one of the most valuable and important abilities of an organization is to adapt to the dynamic environment. People involved in business process management and business processes reengineering believe that implementing process-oriented structures will help organizations to be more open to the changes that the environment requires. In order to be implemented a process-oriented structure, a definition of the term "*business process*" must be adopted. Many definitions are focused on the product that the organization provides for its customers. Below are a few, defined by some of the founders of the idea of business process management.

In 1993, Davenport [1] gave the following definition for a business process: "a structured, measured set of activities designed to produce a specific output for a particular customer or market. It implies a strong emphasis on how work is done within an organization, in contrast to a product focus's emphasis on what. A process is thus a specific ordering of work activities across time and space, with a beginning and an end, and clearly defined inputs and outputs: a structure for action. ... Taking a process approach implies adopting the customer's point of view. Processes are the structure by which an organization does what is necessary to produce value for its customers."

Several years later, in 2009, Hammer and Champy [2], upgrade the definition of Davenport and define the business process as "a collection of activities that takes one or more kinds of input and creates an output that is of value to the customer".

While Davenport is focused on the steps that should be taken while producing the product, the second definition states simply "a collection of activities". However, both definitions agree on the idea that there is input information and output product as a result.

[3] describes business process summarily: "a collection of activities performed to satisfy the customer" and [4] states that the business process is a set of partially ordered activities, designed to achieve a goal.

Although short and clear, both definitions emphasize the set of activities and not paying much attention to the final product.

According to [5] the history of the business in the last few decades can be summarized by asking a few questions:

- the 60s - how to produce more (quantity)
- the 70s - how to produce cheaper (cost)
- the 80s - how to produce better (quality)
- the 90s - how to produce faster (time)
- 21 century - how to offer more (services)

[6], in 1992, notes that it is possible to use mathematically structured programs in some processes performed manually by humans. The author has borrowed the idea from the software industry. This is one of the first interpretations of the term "*business process*" which presents the idea of using machine learning in business.

A. Business Intelligence, systems, and analysis

The concept of business intelligence means a variety of tools, technologies, and skills, designed to extract useful information from a set of big data. These types of systems originate from the Gartner Group in 1996 [7].

Business analytics and analytical processing is a general concept of methods and techniques for data collection, processing, and analysis that aims to enable organizations to make better and informed choices [8]. Business analytics can be grouped into three groups: 1) discovery of information and knowledge, 2) decision support in intelligent systems, and 3) visualization [9].

According to [10] the management of business processes is a concept of controlling, adapting, and optimizing processes. The goal of process management is to increase productivity. Business Performance Management is a system that monitors processes in real-time, notifying managers when a problem or a threat to the optimal work process arises. With the help of such systems, potential areas of improvement and growth can be found. They can be used also for planning and

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prediction, problem identification, setting priorities, resources allocation, setting strategic goals [8].

B. Data Mining

Data mining is a process of identifying and pattern recognition in order to solve a business problem. It can be done with the help of statistical analysis and machine learning and the data can come from various sources - documents (both physical and digital), video and audio files, images and photos, sensors (IoT), wearable devices, emails, clients reviews from social media and so on. The data can also be of various types - structured, unstructured, semi-structured.

When talking about data mining in business intelligence, it is meant classification, evaluation, forecasting, time-series analysis, clustering, natural language processing, shopping cart analysis, and more [11].

III. Challenges in the Implementation and Use of Machine Learning

Many authors pay attention to the challenges in the use of machine learning in business processes [12] [13]. The challenges could be divided into several groups.

A. Ethics

Although machine learning is seen as an innovation, that has a very broad application and the potential to greatly improve the quality of life, there are serious disputes about the ethical part of its usage. Even created with good intentions, a machine learning model can raise many ethical issues and undermine the prestige of the organization that uses it. In recent years, we have witnessed quite a few such cases and research on the subject.

In his book, Life 3.0 [14], Max Tegmark addresses some issues related to the usage of machine learning and artificial intelligence in cases such as prison sentencing, deciding whether to shoot down an enemy aircraft, creating "ethical" robots that attack only enemies but protect peaceful people, etc.

Ethical questions in machine learning can arise in every step - data collection, cleaning and pre-processing, problem definition, model training, and finally, model deployment.

In the step of data collection, the organization that will use the model should comply not only with legal laws and regulations but also with moral ones. While training the model, it will be trained only with the data that is given, meaning that is completely dependent on the data, in particular the people who have gathered and processed it. For example, a model whose purpose is to detect and recognize people can completely fail for one race if it is trained only with images of people from a different race.

In [15] the authors address the problems of facial recognition by creating their own model for evaluating facial recognition algorithms, which they use to evaluate the API services of Microsoft, Amazon, and Clarifai. Some of the evaluation criteria include gender, age, skin color, facial expression. In [16] the authors use a system for skin classification, which is approved and used by dermatologists, to evaluate three commercial services for facial recognition. The results show that the service of IBM wrongly recognizes up to 34.4% black males and females. This research is one of the first in the area.

A characteristic of machine learning is that the more data is collected and used for training, the more accurate the model is. However, when the data is influenced by external factors or is so large that it cannot be checked and filtered, there is a high probability that the model will bias.

In March 2016, Microsoft released their first Twitter bot, Tay. Less than 24 hours later the company is forced to stop the bot because its tweets have become racist, sexist, and anti-Semitic. The training of the bot is based on its interaction with other users of the platform [17]. What Microsoft engineers have not anticipated is that this gives the model access to data that has not been checked and verified. Later, Microsoft states: „Unfortunately, within the first 24 hours of coming online, we became aware of a coordinated effort by some users to abuse Tay's commenting skills to have Tay respond in inappropriate ways".

In [18] the author claims that the algorithms for machine learning and artificial intelligence should reflect the ethical principles of the people, working in the organization that uses them.

B. Quantity and quality of the data

When talking about applications of machine learning in business organizations usually it is meant medium to a large organization that can afford the implementation cost of such algorithms. Except for the implementation cost, there is another reason why these technologies tend to be used by larger companies - the quantity and quality of the data.

As stated in [19] [20], the machine learning algorithms work with big sets of data. To be able to train a model, a big set of data that is processed in a way that is most valuable for the model is needed. However, if the data is not enough, the probability of errors increases.

A lot of small businesses, and even medium and large ones, are still not fully digitalized. Their processes are manual, and the data from pre and post-operation are recorded on paper. Even if the business is digitalized, the probability that the data from previous periods, the historical data, is not. This limits the efficiency and usefulness of machine learning.

Even if there is enough data, that does not mean the data is of good quality and can all be used. In many cases, there is a need for some pre-processing of the data. According to [21] the quality of the data decreases with the increase of the number of data sources and types. In [22] the authors are noting the importance of using quality data when training a model which will be implemented in real-life scenarios and situations. While in the training, stage is important to have enough credible data, it is imperative to use such data when using the model in real life.

C. Cost-benefit

According to [23], in 2020 the percentage of American companies using some form of artificial intelligence - computer vision, natural language processing, audio recognition, etc., is 8.9%. The report also shows that mostly large companies (more than 250 employees) take advantage of such technologies - 24.8%.

Many businesses have not yet reached the idea of using machine learning in their daily processes. Managers must have a clear idea about the usage, cost, and return of such technologies [12]. Their usage should be in line with the business and its needs and not only because of a trend.

Investing time and resources in the implementation of something, just to realize that is not applicable to a particular business will certainly lead to more costs than revenues.

IV. Choosing an Algorithm for Machine Learning

Even though machine learning can be divided into several groups, the algorithms in these groups are endless. Every algorithm can have multiple modifications and variants. This variety makes it difficult to choose a suitable algorithm. Often one algorithm is suitable for one problem but completely inapplicable for another [24]. In such cases, the usage of several models is needed.

An important factor when choosing an algorithm for building a model is the trade-off between accuracy and interpretability [25].

A. Accuracy

The more accurate the model, the better. The accuracy of the model is determined by the errors that can be avoided (reducible errors) and the ones that cannot (irreducible errors). It should be assumed that the selected algorithm will not be 100% efficient and some of the samples will not be classified correctly.

In order to solve this problem, at least partially, a more suitable algorithm should be found [26]. Meaning that an algorithm that gives less error will be better suited for the problem and data. These types of problems can be solved. But even if there is an algorithm that gives 100% efficiency, there is a chance that there are errors that cannot be avoided - missing data, unprocessed data features, etc. [27].

B. The factor "interpretability"

While for academic and scientific purposes, it is not obligatory for the algorithm to be understandable, that is not the case in businesses. When a manager has to decide on the future of the company based on the results of a machine model, he would want to know how the model came to that decision.

According to [28] an algorithm for machine learning can be defined as understandable if its classification can be explained with a simple set of conditional statements (ex. if-else). [29] gives another definition - an algorithm that can be shown in visual and textual ways. [30] states the algorithm must inspire confidence in the user.

Some organizations have the condition that the algorithm they use is understandable so that the decision it has helped to take can be proven if necessary. That is the case with some banking institutions, which are obliged to give an explanation to the bank's customers in case of a denied loan.

The model of the black box, on which many machine learning algorithms are based does not give a clear idea of its internal mechanisms of work. Simpler algorithms such as K Nearest-Neighbors, Decision Trees, Linear Regression are more likely to be understood by people.

V. Conclusions

From the overview of the implementation and usage of machine learning in business some conclusions can be drawn:

- More than one algorithm could be used in a business organization as usually different problems require different solutions, ex. different algorithms;
- Every machine learning algorithm that is chosen must meet certain criteria, such as 1) being able to handle small sets of data; 2) having small computation resources;
- Missing or incorrect data should not render too much influence on the accuracy of the model;
- The algorithms used for business must be easily understandable.

References

[1] T. H. Davenport, Process innovation: reengineering work through information technology. Harvard Business Press, 1993.

[2] M. Hammer and J. Champy, Reengineering the Corporation: Manifesto for Business Revolution, A. Zondervan, 2009.

[3] I. Jacobson, M. Ericsson, and A. Jacobson, The object advantage: business process reengineering with object technology. ACM Press/Addison-Wesley Publishing Co., 1994.

[4] [4] I. Bider, "Business Process Modelling-concepts," Proc. Pract. Bus. Process Model. PBPM 00, 2000.

[5] A. Lindsay, D. Downs, and K. Lunn, "Business processes—attempts to find a definition," Inf. Softw. Technol., vol. 45, no. 15, pp. 1015–1019, 2003.

[6] B. Curtis, M. I. Kellner, and J. Over, "Process modeling," Commun. ACM, vol. 35, no. 9, pp. 75–90, 1992.

[7] T. Friedman, "How Secure Is Your Business Intelligence Environment?," Gart. Res., vol. 28, 2002.

[8] S. S. Hooi and W. Husain, "A Study on Integrating Business Intelligence into E-Business," Int. J. Adv. Sci. Eng. Inf. Technol., vol. 2, no. 6, pp. 20–24, 2012.

[9] Z. Shen and H. Wang, "Research on e-commerce application based on web mining," in 2010 International Conference on Intelligent Computing and Cognitive Informatics, 2010, pp. 337–340.

[10] J. Vom Brocke and M. Rosemann, Handbook on business process management 2. Springer, 2010.

[11] L. Xu, L. Zeng, Z. Shi, Q. He, and M. Wang, "Research on Business Intelligence in enterprise computing environment," in 2007 IEEE International Conference on Systems, Man and Cybernetics, 2007, pp. 3270–3275.

[12] I. Lee and Y. J. Shin, "Machine learning for enterprises: Applications, algorithm selection, and challenges," Bus. Horiz., vol. 63, no. 2, pp. 157–170, 2020.

[13] M. I. Jordan and T. M. Mitchell, "Machine learning: Trends, perspectives, and prospects," Science (80-.)., vol. 349, no. 6245, pp. 255–260, 2015.

[14] M. Tegmark, Life 3.0: Being human in the age of artificial intelligence. Knopf, 2017.

[15] I. D. Raji, T. Gebru, M. Mitchell, J. Buolamwini, J. Lee, and E. Denton, "Saving face: Investigating the ethical concerns of facial recognition auditing," in Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society, 2020, pp. 145–151.

[16] J. Buolamwini and T. Gebru, "Gender shades: Intersectional accuracy disparities in commercial gender classification," in Conference on fairness, accountability and transparency, 2018, pp. 77–91.

[17] M. J. Wolf, K. W. Miller, and F. S. Grodzinsky, "Why we should have seen that coming: comments on microsoft's tay 'experiment,' and wider implications," ORBIT J., vol. 1, no. 2, pp. 1–12, 2017.

[18] M. Turilli, "Ethical protocols design," Ethics Inf. Technol., vol. 9, no. 1, pp. 49–62, 2007.

[19] L. Zhou, S. Pan, J. Wang, and A. V Vasilakos, "Machine learning on big data: Opportunities and challenges," Neurocomputing, vol. 237, pp. 350–361, 2017.

[20] J. Qiu, Q. Wu, G. Ding, Y. Xu, and S. Feng, "A survey of machine learning for big data processing," EURASIP J. Adv. Signal Process., vol. 2016, no. 1, pp. 1–16, 2016.

[21] I. Lee, "Big data: Dimensions, evolution, impacts, and challenges," Bus. Horiz., vol. 60, no. 3, pp. 293–303, 2017.

[22] G. Katz, A. Shabtai, and L. Rokach, "Adapted features and instance selection for improving co-training," in Interactive Knowledge

Discovery and Data Mining in Biomedical Informatics, Springer, 2014, pp. 81–100.

[23] N. Zolas et al., "Advanced Technologies Adoption and Use by US Firms: Evidence from the Annual Business Survey," 2021.

[24] L. Kotthoff, "Algorithm selection for combinatorial search problems: A survey," in Data Mining and Constraint Programming, Springer, 2016, pp. 149–190.

[25] J. T. Operskalski and A. K. Barbey, "Risk literacy in medical decision-making," Science (80-.)., vol. 352, no. 6284, pp. 413–414, 2016.

[26] P.-X. Loeffel, "Adaptive machine learning algorithms for data streams subject to concept drifts," Université Pierre et Marie Curie-Paris VI, 2017.

[27] J. Gareth, W. Daniela, H. Trevor, and T. Robert, An introduction to statistical learning: with applications in R. Spinger, 2013.

[28] G. Valdes, J. M. Luna, E. Eaton, C. B. Simone, L. H. Ungar, and T. D. Solberg, "MediBoost: a patient stratification tool for interpretable decision making in the era of precision medicine," Sci. Rep., vol. 6, no. 1, pp. 1–8, 2016.

[29] M. T. Ribeiro, S. Singh, and C. Guestrin, "Why should i trust you? Explaining the predictions of any classifier," in Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining, 2016, pp. 1135–1144.

[30] B. Kim, "Interactive and interpretable machine learning models for human machine collaboration," Massachusetts Institute of Technology, 2015.