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PERSPECTIVES ON THE USE OF DEEP LEARNING IN BUSINESS

Abstract: This paper presents the perspectives on the use of deep learning in business domain. It treats the actual context, the traditional decision support tools and fucntionalities and the present deep learning models possible to use in business. It actually raises the main points of interest of today's business world always dynamic, always online, dealing with lots of technologies and lots of data. Artificial neural networks are designed such that they can identify the underlying patterns in data and learn from them. They can be used for various tasks such as classification, regression, segmentation, and so on. This paper treats the problems that decision-makers addresses with deep learning models.

Keywords: deep learning, decision support systems, machine learning, business, data mining.

JEL Classification: M15, O33, O32.

Introduction

Deep learning has actually been around for decades, but only in the last few years has it become computationally feasible on a large enough scale to make it an effective option. (Hsu A., 2017)

The concepts and methodologies behind artificial intelligence are not new. Known techniques are used in different ways to achieve new and extraordinary things. It's made possible today by some key factors in the advancement of technology and business, namely:

Computational hardware advancement: Over the last two decades, technological advancement in computational hardware has drastically improved, allowing for general access to powerful hardware at cheaper costs. Contrary to popular belief, AI algorithms utilize the GPU (Graphic Processing Unit) in a computer, not the CPU (Central Processing Unit). Historically, the GPU was required for playing the latest games, however, the architecture is well suited for algorithms that make AI possible.

Lots of data to work with: The catalyst that makes artificial intelligence and machine learning possible is data. The more data an algorithm has to work with, the more refined it can become. The terms big data, and data mining boomed in the recent past. Data collected via various mechanisms on various things, and uncovering insights on that data, provides a solid foundation for artificial intelligence and machine learning. With that said, understanding, cleansing, and preparing data is crucial step in implementing most artificial intelligence algorithms successfully.

Business opportunities: Businesses strive to make a profit. If an initiative adds no value to the business and does not contribute in some way or another towards increasing profit, a business won't adopt it. Given the amount of data businesses have acquired, new use cases and opportunities have emerged with the potential to make profit. This makes AI a feasible area to experiment in, even if it's simply a tool used to understand a business, its offerings, and its customers.

Given a current state with known data, an algorithm is able to determine the best decision in its context.

Deep learning is a term that sounds very mysterious and complex, and it is to an extent. It is similar to machine learning in that it classifies things and discovers patterns in data, however, deep learning algorithms constantly improve their knowledge on what they have already learned in the past. These algorithms may consist of chaining a number of different AI approaches to achieve its goal.

Business computer-based decision support

Deep learning is considered a subset of machine learning (ML) as a whole, an approach to Artificial Intelligence (AI) that enables applications to more accurately predict outcomes without being specifically programmed. About 15 years ago, spam filters started shifting from a rules-based system (e.g. "Move emails from Nigerian Princes into the spam folder.") to machine learning-based filters. A simple Bayesian ML algorithm could learn from a large "spam" training set in which words, headlines, and IP addresses were most likely to indicate that an email was spam.

Individuals differ by their ability to understand complex ideas, adapt to the environment, learn from experience, engage in varied forms of reasoning, and overcome obstacles. Although differences may be substantial, they are never fully consistent: a person's intellectual performance may vary in different situations, in different areas, depending on different criteria. Defining the concept of intelligence seeks to clarify and organize the complex set of phenomena that characterize it. „Rather it is... the ability to acquire and apply knowledge and skills". Organizations differ in their capacity to understand the environment, to adapt to the environment, and to the ability to innovate.

During time and, especially in the last year, researchers and business invested efforts in developing intelligent machines, intelligent artefacts, or intelligent systems (in the sense of a computer application running on a computer). Manifesting intelligence by a machine means an adaptive, anticipate and learning behavior.

A smart system must be a system capable of adapting to new information and learning from changes. The “adaptive” and “smart” concepts should be redundant. An intelligent adaptive agent is able to teach, reason, and prevent absurdities just as people recognize contradictions.

In the 1960s, information systems for procurement, billing, stock control, payments and wages were developed. The purpose of the first Information Systems Management Systems (MIS) was to deliver useful information to decision-makers. Unfortunately, only a few of the developed systems proved to be successful. (Ackoff, R.L., 1967) It was assumed that the main reason was the computer misunderstanding of managerial work. The information system can be seen as any combination of people, hardware, software, communication networks and data resources that store and retrieve transform and disseminate information in an organization (O’Brien, J., et al., 2006). Information systems use a variety of technologies, and their evolution has been fulminating, with a strong integration trend, to the proposition of a global information system. Today, most organizations are aware that in order to maximize the value of the information they hold on their integrated business management (ERP) systems, it is necessary to extend ERP architectures with decision support functionality (Hurbean, L., 2005).

The term Decision Support System was first published in 1971 in an article signed by G. Morton and S. Morton. The authors have built a framework for improving information systems for leadership by using the taxonomy of decisions made by H. Simon. In 1978, the same authors stated that the purpose of these systems is to assist semi-structured decisions (Power, D.J., 2007).

Personal decision-support systems are small-scale systems developed to assist a decision-maker or a small number of independent decision-makers for the same decision-making task. At that time, the emphasis in management science was on integration, efficiency and control. After 1970, the focus was on democratizing the decision-making process by empowering decision-makers. Decision support systems followed this philosophy of supporting decision makers rather than the organization. A major difference between management information systems and personal decision support systems is that they have been successful. In 1980, S. Alter (Airinei, D., 2006) developed a taxonomy of decision support systems that remained valid today, and very useful in classifying today's decision-support solutions such as business intelligence and customer relationship analytics. The current term used for personal decision support systems is analytics.

Decision support systems use: 1) analytical models; 2) databases; 3) decision makers' judgments and 4) an interactive IT modeling process for assisting semi-structured decisions. (O’Brien, J., 2006) Unlike management information systems, decision support systems contain a database model beside the database. The model base is a software component consisting of models used by analytical and computerized routines and which expresses mathematically relations between variables. The use of decision support systems involves four analytical modeling activities: 1) what-if analysis; 2) sensitivity analysis; 3) goal-seeking; 4) optimization analyzes.

Sensitivity or sensitivity analysis is a special case of what-if analysis, which aims to determine the degree of influence that a variable can have on the other variables.

Intelligent decision support systems are decision support systems that have implemented artificial intelligence techniques. They are often called knowledge-based decision support systems. They can be classified into two generations: expert systems belong to the first generation; the second generation is represented by neural networks, genetic algorithms, and fuzzy systems. Techniques of artificial intelligence have been integrated into personal decision support systems, group decision support systems, or information systems for executive management. This is the particular case of data mining and CRM technologies.

Executive Management Assistance Systems (EIS) are data-driven decision-support systems that provide reports on the nature of the organization to management. Despite the title, they are used at all levels of driving. The development of these systems was allowed by client-server architecture, networks and multidimensional modeling of data. The multidimensional view of data or the data cube constituted the basis for the development of the first executive management assistive systems. In the mid-1990s, executive management support systems were influenced by the emergence of systems called Business Intelligence. Dashboard-style interfaces, balanced scorecard reports have changed the executive management support systems. There are authors who use the term Business Intelligence to cover the full range of decision-support information solutions. However, Business Intelligence is the contemporary version of EIS (systems that focus on managerial reporting, data and models).

Business Intelligence tools group: reporting systems, analysis and query tools, performance management tools (dashboards, alert tools), analytical applications. Data warehouses have emerged as a response to the phenomenon of globalization and are database collections that provide information to decision-makers through personal decision-support systems and executive information systems.

In many applications of artificial intelligence applications, the aim is to develop a model of expertise held by an expert and to implement this model as an expert system. The subject of the study is usually a task performed by an individual expert decontextualized by the problem environment; most implementations do not concern the social and organizational context of the decision-making process. The main individual systems and the support they offer are shown in Table 1. None of them provide full and integrated support for all phases of decision-making.

Table 1. **Individual decision support systems**

System	Functionalities
DSS - Decision Support System	Criteria, selection, alternatives, scenarios
Executive Information System and Geographic Information System	Information; criteria, events
Knowledge-based systems	Selection
Learning based systems	Logical evaluation of decision alternatives
Creativity based systems	Decision design; decision implementation plan

Source: Mora, M.

In some cases, some functionality of these systems is unnecessary. For complex and weakly structured issues, the decision-maker needs support at all stages of the decision-making process. Researchers have sought to integrate the functionalities of different individual systems into developing systems capable of helping decision-makers at all stages of decision-making. These are shown in table 2.

Table 2. **Decision support integrated systems**

System	Type	Functionalities
Intelligent decision support systems	DSS+KBS	Developing decisional alternatives, describing the relations between criteria, alternatives and scenarios; selection
Executive Support System	DSS+EIS	Information; developing decision criteria; specifying decision criteria; identifying uncontrolable eventsl specifying the relations between criterias, alternatives and scenarios; selection
Group Decision Support Systems	DSS	Information, design, selection
Management Support System (MSS)	DSS, EIS and KBS	Information

Source: Generalized by the author

The model-based approach allows you to target the decision maker. The decision maker can define the model by using the allowed data structures of the application. In the case of an expert system, the user can edit the rules of reasoning using facts declared by the user as true and defined on the related data structures.

Recognized as cutting-edge information technologies, intelligent technologies or knowledge technologies have become more and more current tools for accountants. We are talking about expert systems, genetic algorithms, neural networks, multiagent systems and hybrid systems, increasingly used in informational-decision modeling, essential in setting up the new stage of evolution of the information society towards the knowledge society.

In the economic field, problem solving with smart technologies concerns (Haag, S., et al., 2006):

- accounting: tax planning, consultancy, professional training;
- audit: mission planning, risk assessment;
- human resources management: to help managers determine if the methods and policies used are in line with the legislation;
- financial management: fund management, forecasting, financial markets valuation, support investment decisions;
- production: to support product categories.

The areas of applicability of artificial intelligence are those in Figure 1.

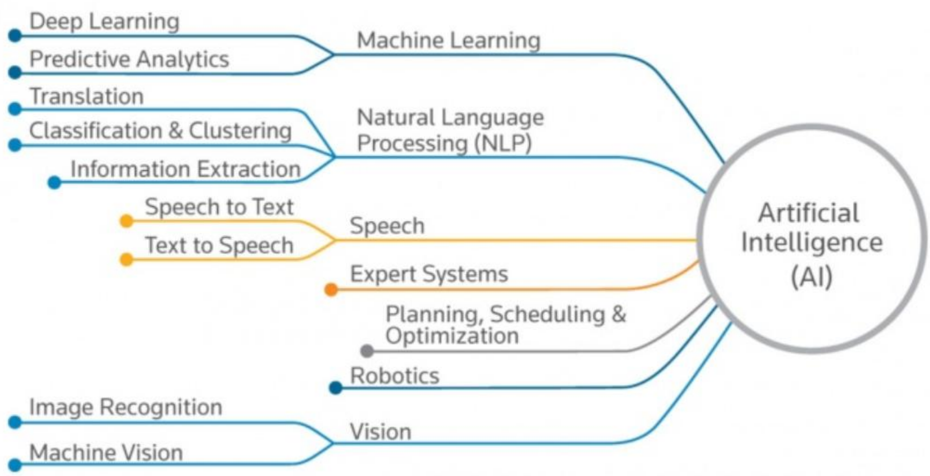

Figure 1. **Artificial Intelligence applicability**
Source: Martin Kingsley, 2016

The computer-based tools to assist the managerial activities are presented in table 3.

Table 3. **The main characteristics of the decision support tools**

Category	The purpose	Users	Results	Operaţii efectuate	Orientarea în raport cu timpul
Transaction Processing Systems	Data processing	Decision makers	Reports	Queries	Past
Decision	Assisting	Decision	Alternatives,	Online	Online or

Support systems	semi-structured decision problems	makers	choices	analysis, reporting, simulations	prospective
Intelligent solution	Assisting complex decision problems	Decidents, not necessarily experts	Recomendations	Inferences	Prospective

Source: Nicolescu, O., Sistemul informaţional-managerial al organizaţiei, Economică Publishing House, Bucureşti, 2001, p. 241

In our opinion, embedded systems based on rules must also be implemented in order to organize information, semantic integration and, of course, to organize in a meaningful way the information must have implemented at the user interface level capable of inferential motors to execute the knowledge extracted from the decision-maker. The IT implementation of the decision models should materialize in a system that: 1) analyzes the current situation of the system to detect alarm states; 2) Perform "what if?" Simulations and 3) provide solutions to the issues raised by the "what if?" Simulations. From the point of view of learning, a computer model can contain learning algorithms. A neural network model or genetic algorithm contains an automated learning algorithm describing the behavior of data stored in the database. Both data mining models and neural network models and genetic algorithms act on small data sets. Automatic learning algorithms of data mining technology are algorithms taken from artificial intelligence and use to discover relationships and develop a model to be used in predicting predictions.

In general, in the construction of computer models, the choice of representation techniques is made according to the balance between the data and the knowledge of the decision making. If more knowledge than data is available then inference on the basis of the knowledge represented is appropriate. If more data than knowledge is available, fuzzy or neural operators are better suited. If data is labeled, supervised learning algorithms are used. If the available data are not labeled, unsupervised learning algorithms are better suited. In reality, situations are presented in a hybrid manner. Typically, insufficient data and knowledge are available, and it is necessary to use data to develop "knowledge discovery" relationships or the use of knowledge to improve data relations. In order to achieve a finer demarcation, we try to address the following question: why specific knowledge rather than information (the result of a function evaluation)? Because the value of the function derives from the general knowledge and input data considered true by the user (premises). For information to make sense, it must therefore fit into a general reasoning template so that it is sufficient to trigger an action (not necessary, but only sufficient).

Conclusions

Machine learning can give an answer by recognizing and sorting out patterns from the data provided and then classifying that data into the possible appropriate pattern (predicting).

Potentially, there are two types of limitations with machine learning: • An algorithm can only work well on data with the assumption of the training data - with data that has different distribution. In many cases, the learned model does not generalize well. • Even the well-trained model lacks the ability to make a smart meta-decision. Therefore, in most cases, machine learning can be very successful in a very narrow direction.

Hence, deep learning took the approach of making each layer learn in advance. This is literally known as pretraining. In pretraining, learning starts from the lower-dimension layer in order. Then, the data that is learned in the lower layer is treated as input data for the next layer. This way, machines become able to take a step by learning a feature of a low layer at the low-grade layer and gradually learning a feature of a higher grade.

Machine learning can be broadly classified into supervised learning and unsupervised learning. The difference between these two categories is the dataset for machine learning is labeled data or unlabeled data. With supervised learning, a machine uses labeled data, the combination of input data and output data, and mentions which pattern each type of data is to be classified as. When a machine is given unknown data, it will derive what pattern can be applied and classify the data based on labeled data, that is, the past correct answers.

On the other hand, with unsupervised learning, a machine uses unlabeled data. In this case, only input data is given. Then, what the machine learns is patterns and rules that the dataset includes and contains. The purpose of unsupervised learning is to grasp the structure of the data. It can include a process called clustering, which classifies a data constellation in each group that has a common character, or the process of extracting the correlation rule.

Neural networks are a little different to the machine learning algorithms. While other methods of machine learning take an approach based on probability or statistics, neural networks are algorithms that imitate the structure of a human brain. A human brain is made of a neuron network.

The applicability of deep learning in business is a research field that promises to learn patterns from data in a supervised or unsupervised manner. The field presents high interest both for practitioners, as for researchers. Deep learning relates to artificial neural networks with multiple hidden layers, convolutional neural networks, recurrent neural networks, self-organized maps, Boltzmann machine and autoencoders.

The applicability in the business field is well investigated. The approaches are in the field of customer relationship management, human/

talent resource, financial analysis, fraud, bankruptcy, supplier relationship management. Churn prediction, identifying the potential outliers or recommending products/ ideas/ customers/ suppliers are well suited as implementation.

Data dimension reduction is an important step for customer classification modeling, and feature selection has been a research focus of the data dimension reduction field (Xiao, J., et al., 2017).

Class imbalance brings great challenges to feature selection in customer identification, and most of the current feature selection approaches cannot produce good prediction on the minority class (Zhu, B., et. Al., 2017).

The product review plays an important role in customer's purchase decision making process on the e-commerce websites. Emotions can significantly influence the way that reviews are processed. The importance of discrete emotions embedded in online reviews and their impact on review helpfulness is not explored intensively in prior studies. This study builds a helpfulness predictive model using deep neural network and investigates the influences of emotions that contribute to review helpfulness. We present an approach that extract novel discrete positive and negative emotion features from textual content of product reviews using NRC emotion Lexicon. In addition, the type of product, reviewer, visibility, readability, linguistics and sentiment related characteristics are also used for comparison and helpfulness prediction. (Malik, M. S. I.; Hussain, Ayyaz, 2017)

The credit scoring aim is to classify the customer credit as defaulter or non-defaulter. The credit risk analysis is more effective with further boosting and smoothing of the parameters of models. The objective of this paper is to explore the credit score classification models with an imputation technique and without imputation technique. However, data availability is low in case of without imputation because of missing values depletion from the large dataset. On the other hand, imputation based dataset classification accuracy with linear method of ANN is better than other models. The comparison of models with boosting and smoothing shows that error rate is better metric than area under curve (AUC) ratio. It is concluded that artificial neural network (ANN) is better alternative than decision tree and logistic regression when data availability is high in dataset. (Imtiaz, Sharjeel; Brimicombe, Allan J. 2017)

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