ANALYSIS, IMPLEMENTATION AND USE OF PREDICTIVE DATA IN BUSINESS MODELS USING THE CONCEPTS AND PARADIGMS SPECIFIC TO THE SCIENTIFIC COMPETENCE FIELD OF "MACHINE LEARNING"

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ABSTRACT

In an economy of implementing the most recent discoveries of scientific progress, competition and positioning as sustainable as possible, with well-defined strategic development perspectives, we identify in the behavior of economic organizations the development of an innovative interface to the external economic macro environment, the massive data collection component.

A relatively new field in resolving economic issues and improving business models, "Predictive Analysis" develops a multitude of algorithms and statistical technologies, from data selection, to generating predictive models, „Machine Learning" specific approaches, historical analysis and organizational economic performance.

The totality of these data, their consequences, their analysis and subsequent interpretation then become the basis for forecasting and development of strategies for consolidation, growth and development.

Predictive models are the ones that operationalize business concepts and functional business entities identified in organizational economic history, an analysis similar to the traditional S.W.O.T. approach, identifies real and potential risks and opportunities, their analysis and study are particularly useful milestones in the subsequent decision-making process.

Predictive analysis is the scientific tool which provides a predictive scoring for the totality of entities involved in the decision-making process.

For economic business organizations and their top management which is in a process of optimal decision elaboration and searching, predictive analysis plays a determining role in marketing components, financial analysis and management, sales power, production management and organizational analysis structured on profit centers.

Evaluation models process the organizational economic development strategies, proposed algorithms and procedures, partner and competition data, subsequent forecasts are generated with the probability of reaching all the desired intermediate targets and the final one, to which the entire activity of the economic organization is subjected.

KEYWORDS: *deep learning, economic business organizations, machine learning, predictive analysis.*

1. INTRODUCTION

The concept of learning has been imposed on the issues of business models by their interactions within the economic macro-environment, the epistemology of the concept identifies the human individual - human individual, human individual - machine, machine-machine contact.

Limiting the possible future developments and subsequent extrapolations of classical cognitive models, possibly operationally transposable for concrete challenges from a dynamic and globalized

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business environment, has led to a new paradigm of approaching economic performance using tools within Artificial Intelligence, Deep Learning and Machine Learning.
Modern economic issues are confronted with overwhelming inflows of data, the areas of scientific competence mentioned above are capable to provide optimal and transparent responses to this type of challenges, the need to introduce statistical analysis and evaluation tools is obvious, the basic concepts pursued are definitions, processes, business information potential for adopted data models.
Anticipating future events with which organizational strategies are confronted must be transformed into informal decision-making processes that have as their primary goal the improvement to the optimal level of the generated results.
Implementing a process of selecting, capturing, and processing data useful in managerial decision elaboration is one of the major tasks of the top human decision maker.
Machine learning processes, the learning analysis approach, focused on building systems having the capacity to adapt the information content, support strategies, and systemic personalization by capturing, reporting, processing, and managing data on a continuous basis which later enables it through its own economic activity, generating added value as much as possible, which is a development advantage for the economic organization.
The raw collection of information in primary form, raw is followed by an extensive and complex program of analysis and selection-retrieval of information used to make the best possible decision, if possible.
The business models used by top organizational decision-makers are subordinated to the main scientific breakthroughs and the development of digital technology.
The data warehouse processing, together with the new and dynamic domain, called "Predictive Analysis", are the theoretical and practical vectors with the fastest and most spectacular evolution.
In the digital economy, the dynamics and globalization, the emergence of the „Internet of Things", the interconnection of the totality of intelligent technological and economic entities, collects and transfers huge volumes of data, which has led to a fundamental change in the mode of operation of economic organizations, data flows coming from the business environment is one of the last and most complex challenges faced by the top organizational decision-maker.
The evolution from the prevailed raw data to decision-making is presented as follows:

DATA – DATA SOURCES –→ DATA ANALYTICS – –→ INSIGHT – –→ DECISION – DECISION MAKING

Figure 1. Fundamentals of machine learning for predictive data analytics, algorithms, worked examples, and case studies, the mit press, Cambridge, Massachusetts, London, England, 2015
Source: adapted from Kelleher, John D., Mac Namee, Brian, D'Arcy, Aoife

The identification and selection of data considered relevant within the economic organization within the complex decision-making process is structured on an important concept, the "predictive data analysis" subdomain of the data analysis.

2. ELABORATION OF ECONOMIC ORGANIZATIONAL MODELS WITH THE HELP OF DATA USED BY PREDICTIVE ANALYSIS

Using high-precision technology at the economic organization level, enormous amounts of data in structured or unstructured form, influences directly and indirectly the economic performance.
The modern business environment generates externally to economic organizations considerable pressure and constraints on reducing operational costs, improving management processes, increasing economic performance.

As the growth of non-economic applications, but especially the those economic of „big data" are being developed, business models structured on the data concept, „Data-Driven Business Models („DDBMs")" becomes an area of great interest for theoretical research and concrete operational applications.

Force vectors that create this phenomenology are identifiable as: competitive factors, merger and acquisition processes, consolidations, requirements and expectations from clients, increased, demanding regulatory level from the regulator, optimization of current, operational expenses.

We also identify the risks associated with business processes generated by potential lost revenue, reduced economic performance margins and profit, actual and potential customer loss, market share loss.

Economic organizations which are looking for managerial performance and shareholder satisfaction, must provide effective, even optimal responses to improve business models, reducing the risk of change, understanding the real-time behavior of cost processes, with the two constituent components, personnel costs, operational costs of main and secondary activity.

Complex processes are developed that correct the possibility of malfunctions, loss of resources necessary for good operation, maintaining the quality standards of products and services offered to customers, compliance requirements, optimizing the time of implementing algorithms and procedures to generate added value at higher levels.

Simulations are the predictive analysis arguments to overcome and respond effectively to the challenges of the external business macro-environment, processes that provide specific services are particularly complex, with varying degrees of uncertainty, interdependent between them.

A factor favored in this approach is the isolation of the studied economic entity, the testing and simulation of potential enhancements, causing major intensity disturbances in the external environment.

The present study addresses the process of developing a baseline and structural orientation, where a business model is operational, it is always transformable, or can apply its own Data_driven Business Models ("DDBMs").

This process is done uniquely and originally or is a takeover, followed by the adaptation and upgrading of an already existing model, the economic organization benefits from previous successful management experience.

Developing a business model for data-driven economic operation involves answers to some fundamental questions:

(1) The ultimate goal pursued by using "Big Data";
(2) Identification of the desired offer wanted by the top organizational decision-maker;
(3) Identification of useful data, acquiring them;
(4) Processing and transformation into into operability of useful data;
(5) Quantification of economic performance obtained with this type of data in financial results;
(6) The barriers and constraints encountered in reaching the final target;

Applications through predictive analysis using simulation models allow the validation of innovative and improved ideas, buy-ins from potential customers, with no disruption of processes generated by risk, variability and interdependence over time, fast and simple access for decision makers to already existing data, reduction of risk to minimization, optimization of operational times, real evaluation of process capacity performance, reduction of process cycles, financial optimization and human resources.

These top, innovative technologies, give a fresh insight into the perspectives over the decision-making processes, leading implicitly to increased productivity of selected business models, a rigorous process of operational costs optimization is also induced.

The process of organizational predictive analysis is anchored in several representative hubs, of which we recall, artificial intelligence, machine learning, data mining, statistical algorithms.

By setting up economic forecasts on the historical background of the analyzed economic organization, predictive strategic trends provide improved results, with a relevant degree of precision, to improve the business performance of each economic entity.

Electronic commerce, e-commerce is a very generous domain for predictive analysis applications, the giants in this area, increasing their sales force by using this new concept.

In this type of application, the behavior of the final customer, „end-user" behavior is developed through social media channels, the online activity of web site visitors, offering research paths and suggestions for all interests of potential users and real users.

Machine learning, at concept and paradigm level, needs to be strategically developed and operationally transposed by three structural entities:

(1) **Learning-instruction data:** data are labeled, classified and sorted by the human decision maker;
(2) **Software Structure:** the software application library that develops machine learning models by evaluating the set of training data;
(3) **Hardware Structure:** the central processing unit of the computer, C.P.U. (Central Processing Unit) and GPU (Graphics Processing Unit) memory unit specializing in graphic applications and image processing and video applications.

Transposition into operation of analytical predictive data makes identifiable the following economic entities considered to be representative:

(1) **Dosage prediction:** is a specific medical management process, predictive analysis models are used to establish optimal dosages based on dosages used in the past, and generated associated results;
(2) **Risk assessment:** the economic organization is influenced by several key factors in its operational-strategic activity, the risk is one of following, the use of predictive analytical models is a very effective tool for top decision makers to develop a more accurate prognosis regarding risk prediction, the model is "trained" using the data of the organizational economic history;
(3) **Price prediction:** the prices in a dynamic and competitive economic environment have their own evolution, they are influenced by a multitude of criteria, such as seasonal changes, variable demand, special events within the specialized market, predictive analysis models are trained to base the forecasting of pricing at their optimal level, increasing sales force, maximizing generated added value and related profits, predictive predictions are the hubs on which the organizational strategies on selling prices are elaborated;
(4) **Action models:** The end-user's behavior is the one that influences business management decision-making, anticipating it, leading to an improvement of the process for top organizational decision-management, forecasted data analysis is a vector for the development of behavior patterns that anticipate the behavior of the final consumer based on its economic history;
(5) **Documents hierarchy:** automatic classification of documents is possible with processes and algorithms specific to predictive data analysis, they are positioned in different categories, spam e-mail filtering, feedback messaging type redirection, decisions regarding the human resources department, mode of defining a document is extrapolated to a content of images, sounds, special effects;
(6) **Diagnosis:** for some professions, scientific researchers, doctors, engineers, diagnostic analysis is a fundamental part of professional competencies, predictive analysis models are those that help the professional experience of each human entity, leading to better results, leading to enlargement of the successfully solved cases, the diagnostic analysis based on the predictive analysis models becomes a usual and mandatory procedure in these cases.

3. ADDRESSING ISSUES THROUGH THE CONCEPTS AND PARADIGMS OF MACHINE LEARNING

The concept and operational and strategic paradigms developed by Machine Learning offers computers, regardless of the processes they use, scientific, technological, economic, learning ability, whether or not programmed for this cognitive perspective.

The learning process in the Machine Learning concept is defined as a complex, automated process that implements the identification and extraction of data patterns (traces, their patterns), the process of learning is the one that identifies, analyzes and explores the development of learning algorithms and makes predictions data.

The developed models are based on sampling inputs, Machine Learning processes are initiated when programming of explicit algorithms is difficult to achieve, an efficient filtering process is developed, spam emails are removed within this approach, unauthorized intruders in the network, an effective data protection process is implemented.

In the specialty literature and in current practice there are three significant typologies of Machine Learning: unsupervised learning, semi-supervised learning, rigorous, reinforcement.

4. MACHINE LEARNING APPLICATION, INVESTMENT ON THE CAPITAL MARKET

In the following it is presented synthetically the history of a portfolio of investments in the capital market, open economic organizations, their main object of activity.

Table 1. Fundamentals of machine learning for predictive data analytics, algorithms, worked examples, and case studies, the mit press, Cambridge, Massachusetts, London, England, 2015, p.4

DIMENSIONALITY OF INVESTMENT				
Running number	**Activity**	**Economic History**	**Ratio**	**Profit Generation OUTCOME**
1	energy sector	5	2.99	profitable
2	manufacturing sector	7	4.22	unprofitable
3	manufacturing sector	5	3.22	unprofitable
4	manufacturing sector	10	3.05	unprofitable
5	energy sector	15	3.90	unprofitable
6	energy sector	10	2.35	profitable
7	manufacturing sector	7	1.40	profitable
8	manufacturing sector	5	1.90	profitable
9	energy sector	8	5.50	unprofitable
10	energy sector	10	4.30	unprofitable

Source: adapted from Kelleher, John D., Mac Namee, Brian, D'Arcy, Aoife

The presentation of the investment portfolio on a stock exchange, shares of economic organizations, provides us with some essential and useful information about the investments made:

- the business domain of the tradable economic organization;
- the economic history from the moment of listing on the capital market, the profit and loss account;
- ratio, represents the relation between the amount invested in the shares of that economic organization and the profit generated by the economic entity;

– the target tracking feature OUTCOME, gives the investor a perspective if the investment target is reached or not, is a clear, rigorous, transparent presentation of the performance of the developed investment portfolio;

For the last of the above-mentioned features, the value generated is from the binary, "profitable", "unprofitable" logic type, this is the most representative feed-back in assessing the investment strategy developed for a specific waiting time.

By positioning us in the specific machine learning approach, each row in the dataset is called the learning instance, "training instance", the set of data, in general, is called a set of data (set) for training, learning.

The implementation of the predictive model in an operational computer structure is presented below:

$$\begin{aligned}
&\textbf{\textit{if RATIO}} - \textbf{\textit{DIMENSIONALITY OF INVESTMENT}} > 3\ \textit{then}\\
&\textbf{\textit{OUTCOME}} = \textbf{\textit{unprofitable}}\\
&\textbf{\textit{else}}\\
&\textbf{\textit{OUTCOME}} = \textbf{\textit{profitable}}
\end{aligned}$$

Figure 2. Fundamentals of machine learning for predictive data analytics, algorithms, worked examples, and case studies, the mit press, Cambridge, Massachusetts, London, England, 2015, p.4

Source: adapted from Kelleher, John D., Mac Namee, Brian, D'Arcy, Aoife

We assert that this model is compatible with the set of data, there is no state in the set (data set) for which the developed model does not make a correct prediction.

When a new investment strategy is translated into operationality, the predictive model of the investment policy, structured on the two components, "unprofitable" and "profitable", the decision is made, based on this prediction.

Machine Learning specific procedures and algorithms structure the learning process of the model that manages the relationships between descriptive features and target characteristics in a data set, extrapolating the developed scientific analysis, we present below a more complex investment picture that addresses the same issue of structuring an investment portfolio in open economic organizations present on the regulated capital market.

The amount is the sum expected to be generated by the economic organization in which it was invested in a time horizon, specified in the portfolio development strategy, the investment reflects the value of the initial potential investment.

The ratio expresses the coefficient of magnitude between these two values, the economic history, the duration when the shares of the economic organization are tradable, the sector, places the economic organization in a certain stock index.

The type of transaction reflects the way of financing, own funds or margin, the degree represents the degree of risk to which the investment model is subjected to each position, evaluation - OUTCOME, presented whether the investment is or not profitable.

The prediction model that uses as a decisive factor the investment ratio achieved, the profitability obtained, is no longer fully consistent with the data set.

The development of the new predictive model compatible with the new set (data set) requires a higher degree of mathematical complexity.

Prevailing, comprehension, and processing of elements give a certain degree of transparency and flexibility that make the chosen model to be algorithmically expressible, subsequently higher transposable informational.

A possible alternative to the issues raised is presented in the subsequent computer structure.

Table 2. Fundamentals of machine learning for predictive data analytics, algorithms, worked examples, and case studies, the mit press, Cambridge, Massachusetts, London, England, 2015, p.6

DIMENSIONALITY OF INVESTMENT								
No	**Amount**	**Invest**	**Ratio**	**Economic History**	**Sector**	**Trans. Type**	**Risk Type**	**OUTCOME Evaluation**
1	240,000	65,000	3.69	10	manufact.	own equity	medium	profitable
2	82,000	73,000	1.12	5	energ.	own equity	low	profitable
3	205,000	28,000	7.32	5	manufact.	own equity	medium	unprofit.
4	170,000	81,500	2.08	10	energ.	margin	medium	profitable
5	180,000	48,000	3.75	8	energ.	own equity	medium	profitable
6	145,000	58,000	2.5	8	energ.	margin	medium	profitable
7	195,000	73,000	2.67	10	energ.	own equity	low	profitable
8	210,000	78,000	2.69	5	services	own equity	low	profitable
9	85,000	55,000	1.54	10	energ.	own equity	low	profitable
10	190,000	42,000	4.52	5	manufact.	own equity	medium	unprofit.
11	162,000	31,000	5.22	10	energ.	margin	high	unprofit.
12	158,000	87,000	1.81	8	energ.	own equity	low	profitable
13	280,000	46,500	6.02	5	manufact.	own equity	high	unprofit.
14	240,000	53,000	4.52	5	services	margin	high	unprofit.
15	132,000	78,500	1.68	10	manufact.	margin	low	profitable
16	220,000	62,500	3.52	10	energ.	own equity	medium	profitable
17	295,000	180,000	1.63	10	energ.	own equity	low	profitable
18	155,000	85,000	1.82	8	energ.	own equity	low	profitable
19	145,000	95,500	1.51	8	energ.	own equity	low	profitable
20	250,000	65,500	3.81	8	services	own equity	medium	profitable
21	220,000	35,500	6.19	5	manufact.	own equity	low	unprofit.
22	165,000	12,500	13.2	10	energ.	own equity	high	unprofit.
23	285,000	32,500	8.76	10	energ.	margin	high	unprofit.
24	125,000	95,500	1.30	10	energ.	own equity	low	profitable
25	310,000	42,500	7.29	10	energ.	margin	high	unprofit.

Source: adapted from Kelleher, John D., Mac Namee, Brian, D'Arcy, Aoife

By elaborating the predictive model using only the dimensionality of the investment report on the capital market, we notice the characteristic that no longer corresponds to the data set.

It is identifiable a predictive model that provides full concordance with the data set, the mathematical procedure, informational transposed, with a possible operational representation in the following.

$$
\begin{aligned}
&\boldsymbol{if\ RATIO - DIMENSIONALITY\ OF\ INVESTMENT} < 1.5\ then\\
&\boldsymbol{OUTCOME := profitable}\\
&\boldsymbol{else\ if\ RATIO\ \ DIMENSIONALITY - \ INVESTMENT} > 4\ then\\
&\boldsymbol{OUTCOME := unprofitable}\\
&\boldsymbol{else\ if\ \ ECONOMIC\ HISTORY} < 8\ SECTOR := MANUFACTURING\ then\\
&\boldsymbol{OUTCOME := unprofitable}\\
&\boldsymbol{else}\\
&\boldsymbol{OUTCOME := profitable}
\end{aligned}
$$

Figure 3. Fundamentals of machine learning for predictive data analytics, algorithms, worked examples, and case studies, the mit press, Cambridge, Massachusetts, London, England, 2015, p.5

Source: adapted from Kelleher, John D., Mac Namee, Brian, D'Arcy, Aoife

5. OPERATIONAL WITH THE HELP OF MACHINE LEARNING

Machine Learning algorithms are operationalized with the help of a set of predictive models corresponding to the relationship between the descriptive characteristics and the target characteristics of the data set.

The criterion for managing this type of search is to identify data-compatible models, searching for a consistent operational model is not enough to find out the effective predictive models.

Economic organizations are often confronted in their operation with very large volumes of data, there is the possibility of induction within the systemic processes carried out by noise, which leads to the disturbance of the values of the characteristics, the prediction models that are compatible with the data sets accompanied by noises, then generates predictions incorrect, erroneous.

Thus, machine learning projects, along with training data sets, are identifiable with a small number of stable states in the field of activity.

We conclude that the machine learning approach in this concept does not guarantee a unique solution, consistent with all the information available.

So the machine learning approach is inappropriate for such cases, exemplifying, choosing a Financial Analysis Services Company team that wants to develop a full study of the groups of investors in its portfolio after defined criteria such as single individual investors, investors who make investment decisions in the couple, investors who make the investment decision by consulting the entire family, studying and anticipating their investment behavior.

Given that the Financial Services and Investment Companies have enormous amounts of data about the potential and real clients about their economic history and their investment activity in databases and data storage, this kind of classification is an operational practice, the utility of the traditional approach by means and algorithms specific machine learning, initiating a comprehensive and complex debate.

Applying the criterion that is consistent with the model's training data, no relevant indication is identified, which of the developed models are chosen when uncertainties arise out of the plurality of training data, coherent patterns developed become useless for this type of query.

The identification of predictive, performing, flexible models, in accordance with the rigors and constraints imposed by the multitude, data set, is equivalent to developing a process of memorizing the entire set of data.

We conclude that by this type of approach, no learning process is developed, justification is identifiable in the undifferentiated relationship between the descriptive and target characteristics resulting from the elaboration of coherent models.

A predictive analysis model is operational, generating meaningful results, under the condition of producing predictions with a certain degree of rigor, for interrogations that are not identifiable in the multitude, set of data.
Developing a predictive model with a high degree of relevance of the developed process, captures in its operational activity the underlying component between the descriptive and the target components, an extrapolation process is thus initiated.
The fundamental goal of applying the concepts, methods and algorithms specific to Machine Learning approach is to identify and operationally address for the business issue of the predictive data model with the highest degree of generalization, which is adaptable to most types of applications and challenges emerged from the business environment.
To successfully complete the identification of the predictive data model with the highest degree of generalization, the algorithms used by the machine learning use a few criteria to which the candidate models are subjected in the searching process.
In a first approach, the data set consistency is considered to be defining, to select the best predictive model, but proving its applicative margin, the discussion must be extrapolated to other search paradigms.
The existence of a very large set of machine learning specific learning algorithms increases the selection area to identify the best predictive, even optimal model.
Choosing the use of a machine learning algorithm in the detriment of another similar algorithm is basically a change in searching criteria.
The entire selection of searching criteria for choosing a particular type of predictive model consists of identifying a set of assumptions about the model characteristics that we want to be induced by the algorithm.
The multitude of hypotheses (assumptions) which define the criteria for the chosen model of a machine learning type algorithm is known as the "inductive bias" generated by an algorithm that belongs to the machine learning approach.
Inductive learning expresses the identification of a general rule for a finite set of data, machine learning thus gets inductive learning valences, the machine learning algorithm hypothesis used in choosing the best model is called "inductive bias".
We identify two types of inductive bias that the machine learning algorithm uses, a restrictive bias, "bias restriction", and a preferred bias, "preference bias."
"Restriction bias" is the one that generates constraints for the set of models that the machine learning algorithm uses as they go through the main learning process.
"Preference bias" coordinates the learning algorithm in the process of choosing some models to the detriment of others.
Machine learning transposed into operationality is looking for a lot of potential business models, a process of identifying the predictive model that generates the most accurate set of data is developed. The search process is coordinated by algorithms that use two informational sources usable during their operation, a set of training data and an inductive bias are also assumed by them.

6. POSSIBLE INCONVENIENCES INDUCED BY THE USE OF MACHINE LEARNING

Machine learning is an extremely powerful and effective tool in addressing business models issues from a very dynamic and transparent economic macro-environment, but it is not a panacea for the totality of challenges and conditionalities that arise within it.
Using a multitude of coding algorithms, the machine learning approach generates different types of inductive biases, coded inductive influence induces operationalized business models that go beyond the specific states of a multitude of training and learning data, an improper inductive bias subsequently induces a multitude of errors.

It is demonstrated that there is no particular inductive bias usable above the average of the total number of inductive biases, operationally, there is no foreseeable predictive task that significantly influences the inductance process.

The human resources department has to offer individuals with a high degree of professional competence, analyzing and interpreting data in real time, for choosing the machine learning algorithm for a predictive data task.

Organizational performance is conditioned by finding significant data in machine learning processes, business models have the opportunity to become fast, efficient, possibly optimal.

Implementing a proper process of data selection and implementation, allow the release of human, financial, logistic resources, long-time interval allocation, innovative phenomena, new products and services with superior added value allow the approach for new market segments.

Such an evolved form of machine learning algorithm is developed only after the implementation and operation of a correct data selection process, understanding how data categories influence the training-learning process then leads to changing the adopted business model, increasing the level of precision of the prediction and efficiency of automation processes.

We also identify one of the most common causes of ineffective, error-generating patterns, the identified reason is the imbalance of used data, called learning bias.

The inability of the model to identify and manage the relationship between the concrete instances of entry and the desired results is induced by the model that does not respect the learning and training data collection; in this approach the assumptions are simplified until permissiveness for erroneous information appears or a diminished cognitive capacity is allocated.

In addition, the chosen model has the ability to exceed the training-learning data if the information is too large, the evaluation process for delivering the result sought is compromised, the model is erroneous by allocating a too large physical and temporal space data storage and inability to extrapolate the operationality to new challenges and constraints.

However, there is a possibility to calibrate the model for concrete operational cases in the desire to achieve consistent and predictive results, an evolutionary process of models is found, flexibility and adaptability are its fundamental characteristics.

"Deep learning" is the cognitive process specific to a human individual being recognized at the level of computers, the algorithms specific to this new type of approach are developed with the help of programs that handle enormous amounts of data, mathematical data is processed, communication, and visual structures, static and dynamic images - video frames.

In approaches to business models implemented by economic organizations, data is analyzed at the raw input level, the amount of memory allocated, and then correlated with data already residing in the system.

It is how the great social media actors, Facebook, promote the marketing components of the economic organizations that have adopted the respective economic concepts and paradigms.

Deep learning operationalization business has a particularly important strategic development horizon, as an alternative but also with machine learning is an effective and powerful organizational development vector.

We mention in the present debates and scientific analyzes the concept of "take-away" that represents the machine learning process with significant applications in the business environment, it favors improved operations that interact with existing entities, images, text, communication through language.

The approach at this level brings software structures that facilitate communication with final clients, end-users, the approach has as a consequence the increase of the added value promoted in the business environment by the economic organization, the interfaces in the concept of machine learning are those that make computers the main actors in the competitive dynamic imposed by the most extensive process facing human civilization as a whole, globalization.

Structured business models using machine learning are confronted at the transition to operability with two possible errors that affect the generated results, "over-fitting" and "under-fitting", therefore above and below the model of the economic entity.
Induction of under-fitting is observed when the prediction model chosen has a simplistic construction to represent the basic relationship between the descriptive and target characteristics, the over-fitting is a consequence of choosing a prediction model with a very high degree of complexity with a reduced data offer , influenced by noise-induced signals.

7. DEVELOPED AND IMPLEMENTED PROJECTS, PREDICTIVE DATA ANALYSIS APPROACH

The approach of economic projects through the methods and algorithms specific to the predictive data analysis has the chances of achieving the much higher final target if the implementation takes place with a standard management process, operationalized in relation to its life cycle, the implementation of machine learning concepts along with the development of learning processes with automatisms and statistical machines are the new organizational tendencies for transforming the data analysis cycle into a vector and argument for organizational growth.
At this level the data are collected, the important ones, isolated, validated and exploited, with the help of analytical descriptive methods are made primary analyzes, univariate analyzes, data visualizations, highlighting of statistical data and derived variables, subsequent, predictive modeling is completed by identifying the number of methods and technologies, identification of the optimal model, its implementation in the effective organizational operability.
The role of machine learning algorithms, used in complex learning processes, becomes thus fundamental.
The operation of data warehouses, the highly complex technological environment in which the data analysis and processing platform is developed and implemented, are all challenges facing the top decision-management of the economic organization.
One of the most common approaches for predictive data analysis projects is "Cross Industry Standard Process For Data Mining" ("C.R.I.S.P.-D.M."), process which significantly covers predictive data analysis.
We consider it extremely opportune to approach the business model issue using the Cross Industry Standard Process for Data Mining methodology, which does not belong to the property, but promotes operations, industrial technologies, algorithms and visualization techniques, the predictive data analysis process is a dual complex, technical and economical, six synergic operational key entities define the approach of a project through predictive data analysis, the C.R.I.S.P. – D.M. methodology.
The six relevant phases are:

(1) Understanding the business model: Predictive models are focused on intermediate trajectories which lead to the development of the chosen economic organization such as consolidating the client's portfolio of existence, increasing it, increasing sales force, improving the level of efficiency of the induced systemic economic processes, the initial data are fundamental in understanding the chosen business model and its transposition into operability, identifying a set of solutions and optimal proximate solutions;

(2) Understanding the data: how to use the results of the predictive data analysis process induce a further approach to the operational business model, the data analysis process is conducted with the rigorous identification of the available data sources, such as the type of data contained in these sources;

(3) The data preparation process: the development of predictive data modeling processes requires the identification of specific types of data, these are organized into a basic cognitive structure called "analytics base table (ABT)", we find in this process phase all the activities which must be carried out so that the disparate data sources available within an economic organization in an operational ABT with which machine learning models are subsequently induced;

(4) Modeling process: C.R.I.S.P. – D.M.'s operational process modeling is triggered when machine learning operations are triggered; different approaches through these artificial intelligence mechanisms are used to design and develop predictive models, among them the most good, performance, optimal is chosen for implementation;

(5) Evaluation: Before being implemented for transposition into operation for an economic organization, it is important that the chosen model is subject to a complex and total evaluation process, testing the capacity to achieve its purpose is thus mandatory, the capability to cover tasks of the predicate model, issuing rigorous and accurate predictions after launching and avoiding over-fitting and under-fitting influences are all the required conditions;

(6) Effective implementation: the fundamental purpose of the activity of the economic organizations is the one that subordinates the entire activity of the operationalized machine learning models, they cover the whole implemented business model, contributing to its success.

8. ALGORITHMS AND TOOLS USED IN PREDICTIVE DATA ANALYSIS PROCESSES

Business models chosen by economic organizations, regardless of their typology or the particularities of the economic environment in which they operate, allow access to a number of paths to specific machine learning concepts and paradigms for the development of predictive data analysis models.

The economical process of choosing an automated machine learning solution for a particular business model is conditioned by the existence of an application solution or generated by a specialized programming language.

If the choice of business model operation is made with machine-learning facilities based on a specific application or a "point-and-click", developing and evaluating models for related data is a fast-running default process.

The predictive data analysis model is adapted, evaluated and transposed into operational life at very low times, this is a decisive factor that consistently contributes to the managerial performance of the decision taken for the economic organization.

We mention for the predictive data model some of the remarkable solutions used by the major transnational economic organizations, I.B.M. S.P.S.S., S.A.S Enterprise Miner, Rapid Miner Studio, Knime Analytics Platform, Weka.

An emerging alternative for using the basic application solutions for developing predictive data modeling models within the business models is the programming language approach.

When using programming languages for predictive data analysis projects, this approach offers the human operator flexibility, in contrast to application-based solutions, where the results are strictly conditioned by the type of computer tools used.

A second remarkable advantage of using programming languages is access to new types and advanced analysis techniques, before they become operational applications-based solutions.

We also identify associate advantages, one of the drawbacks is that programming requires a high level of training for human resources within the organization, information infrastructure support, database and data warehouse management, access to available application-based solutions are additional tasks aware of software developers who need to develop, adapt and translate into operation this kind of media.

9. CONCLUSIONS

In the analysis and scientific study presented, conceptually translated from artificial intelligence, the machine learning shows its role in the development of predictive data analysis projects, specific machine learning algorithms elaborate and develop the predictive model by inducing a high degree of generality of the set relation of descriptive features and the target characteristic from a specific automated learning-training state.

We note that it is quite difficult to achieve the previous task described due to the existence of a multitude of models structured on the concepts of machine learning, structuring them according to previously defined criteria constituting a process with a higher degree of complexity.

Machine learning algorithms address this type of problem by encoding an inductive bias, so a process of choosing an algorithm in relation to another is initiated.

The totality of other types of approaches, the data used, the descriptive characteristics, the mode of implementation and the operationalization within the chosen model, influences the outcome of the systemic process unfolded.

We conclude that the machine learning approach of predictive data analysis processes in business models specific to economic organizations offers in the case of automated training-learning processes a multitude of solutions, identifying the optimal solution is the main target.

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