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Branko R. Pavlović[1]

CHALLENGES IN APPLICATION OF MACHINE LEARNING IN INSURANCE INDUSTRY

REVIEW ARTICLE

The Internet of Intelligent Things, Blockchain technology[2], software robots[3] and various aspects of artificial intelligence such as machine learning are often referenced in modern literature as having great potential to improve the processes in insurance business. This paper will focus on machine learning.

Machine learning is a subset of artificial intelligence intended for study and recognition of behaviour patterns by using statistical methods for available data processing. In other words, machine learning is a software able to make its own decisions based on previous experience. The key benefit companies can draw from machine learning is prediction of future trends, where software independently discovers patterns in the available data.

Insurance companies may use machine learning to optimize their tariffs, settle claims more efficiently, and improve the quality of loss reserving, and as a powerful tool in combating frauds.

Key words: *machine learning, insurance*

I. Introduction

Machine learning is a method of data analysis that uses specific algorithms to uncover hidden connections in data, without being explicitly programmed to act in order to find these connections. In other words, machine learning is the ability of a computer to find the information that is new to what was known at the time of learning.

[1] President of the Serbian Actuarial Association
E-mail: pavlovic.branko@gmail.com
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[2] Pavlović, B. (2018). Blockchain Technology in Insurance and Reinsurance, the 16th International Symposium *New Challenges in Insurance Market*, Aranđelovac

[3] Pavlović, B. (2019). Robot Usage in Insurance, the 17th International Symposium *Insurance on the Eve of the Fourth Industrial Revolution*, Zlatibor

It is used in face recognition, recognition of objects in images or videos (e.g. X-ray detection of abnormalities), self-driving cars, board games (e.g. chess, checkers, backgammon and go), computer games (e.g. Doom and Counter Strike), quizzes, text classification, translation, social network analysis, speech recognition, etc.

The subject of this paper is the analysis of possibilities for improving the processes in insurance industry by using machine learning techniques and the challenges arising therefrom. The aim is to highlight the benefits that Serbian insurance companies can derive from taking part in one of the trends that the fourth industrial revolution brings upon.

1. Classification of Machine Learning Methods

Machine learning is based on the ability of specialized software to create its own logic and independently notice the connections between data. Three problem-solving methods[4] are used.

1.1. Supervised Learning

It involves forming of a training dataset and using it to teach the software. The links between the data identified in the training set are applied to a new dataset, which the software has not seen before. An example is the classification of tissue into malignant and benign.

The problems solved by the supervised learning method are divided into regressive and classification problems.

In regressive problems, the goal is to connect the entered variables and present the result with a continuous function. One example of the aforementioned is the prediction of real estate prices based on previous experience in monitoring the transactions on the property market.

In classification problems, the goal is to present the result in the form of a discrete output value. An example is handwriting recognition.

The similarities and differences of regressive and classification problems can be explained by the following example:[5] the training set provides the actual sizes of houses with their prices in the training set, and the goal is to predict the house price based on its size. Price, as a function of the size of a home, is a continuous output parameter. Therefore, it represents a regressive problem. However, if the goal is to find out if the house was sold for less or greater than the predicted price, instead of predicting the price of the house, it becomes a classification problem. Subsequently, the houses are classified into two discrete categories, depending on whether they were sold at the predicted price (one category) or not (the other category).

[4] Nikolić, M. and Zečević, A. (2019) *Mašinsko učenje*, Faculty of Mathematics, University of Belgrade

[5] Milovanović, A. (2015). Seminar Paper Mašinsko učenje, Faculty of Mathematics of the University of Belgrade

1.2. Unsupervised Learning

Rather than using a training set, employed are the techniques for uncovering hidden knowledge in the analysed set. The classification of tissues into the groups with similar characteristics may serve as an example[6].

In unsupervised learning, data structures (groups or clusters) may be formed. Clusters are made based on the correlation of variables in the data. The goal is to see the correctness of the data, and there is no feedback based on predicted results, that is, it is not known what is true and what is not. Therefore, a potential solution to the problem cannot be optimized with this method. Clustering is a good method for, for example, tagging documents.

1.3. Reinforcement Learning[7]

Theoretical framework of reinforcement learning is described by Markov Decision Processes. Let us assume that the agent and environment interact only at discrete time t = 0, 1,... At any time t, the agent perceives a finite set S of distinct states S_t in its environment and has a finite set of distinct actions At that it can perform from the finite set of permissible actions A(s) in the particular state „s", receives a reward R_t+_1 from the finite set of rewards R and moves forward to the new state S_t+_1. The main Markov's property is the property that the new state and reward depend only on the previous state and action taken and not on the entire process history.

Rewards implicitly define the agent's goal. They are determined so that in trying to maximize the reward, the agent does the work that needs to be done. The classic mistake is that rewards are used to direct the agent toward how to do something instead of what to do. For example, if an agent plays chess, he should be rewarded if he wins the game, not if he captures an opponent's piece.

II. Literature Review

In the past seventy years, a large number of authors around the world have been exploring machine learning and yet, when it comes to insurance industry, it was not until quite recently that they have begun to address this method of data analysis. In 1959, Arthur Samuel provided an informal definition of machine learning[8], as follows: "The field of study that gives computers the ability to learn without being explicitly programmed." A modern scientific definition[9] was formulated by Tom Mitchell in 1997: „A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P if its performance at tasks in T, as measured by P, improves with experience E."

[6] Novaković, J. (2013). Rešavanje klasifikacionih problema mašinskog učenja, Reinženjering poslovnih procesa, vol. 4, Faculty of Technical Sciences in Čačak

[7] Nikolić, M. and Zečević, A. (2019). *Mašinsko učenje*, Faculty of Mathematics of the University of Belgrade

[8] Samuel, L. (1959). Some studies in machine learning using the game of checkers, *IBM Journal of research and development*, 3(3), p. 210-229.

[9] Mitchell, T., (1997). *Machine Learning*, McGraw Hill and MIT Press, USA

The Table 1 shows the most significant past events in the development of machine learning.

Table 1 Brief History of Machine Learning

Year	Event
1943	McCulloch and Pitts formulated „threshold logic“, a predecessor of neural networks
1950	Alan Turing dealt with learning machines
1952	Arthur Samuel developed the first computer checkers-playing programme
1957	Frank Rosenblatt developed hardware „perceptron“
1963	Vapnik and Chervonenkis proposed the first variant of support vectors
1967	Cover and Hart proposed „k-nearest neighbours“ algorithm applied to the travelling salesmen problem
1975	Werbos formulated backpropagation algorithm for calculating the gradient of a neural network
1981	DeJong introduced explanation-based learning that enabled deriving rules from data
1985	Sejnowski and Rosenberg developed a software able to learn how to pronounce English words
1992	Boser, Guyon and Vapnik proposed the use of kernel with support vector method, making this method predominant in the machine learning of the 1990s
1992	Tesauro developed TD-Gammon, the system for playing the game of backgammon
2006	Hinton introduced the term deep learning for training algorithms for multi-layered neural networks that have been predominant in the machine learning ever since
2011	IBM Watson system faced off against champions of the popular American television quiz show Jeopardy and won!
2012	Google X developed a system able to independently view video recordings on YouTube and identify cats

Year	*Event*
2014.[10]	Facebook system for facial recognition that uses neural networks, DeepFace, scored a 97% success rate.
2016.	Google AlphaGo system beat a world champion in the game series 4-1
2017.[11]	Alphabet's Jigsaw, based on machine learning, managed to recognise and stop on-line trolling
2018.[12]	Improved neural network language model for recognition of spoken languages by introduction of pretrained language model

Source: Nikolić, M. (2018). Uvod u nadgledano mašinsko učenje, Faculty of Mathematics, University of Belgrade

In the insurance industry, the authors have mainly addressed the application of machine learning in defining insurance rates, claims reserving, and combating frauds. In 2019, a group of American authors[10] dealt with the following machine learning techniques: simple decision tree, random forest and boosted trees, on the example of developing tariff plans based on the claims data. In 2016, a Swiss professor Wüthrich explored claims reserving using Chain Ladder method and analysing the behaviour of individual claims by machine learning method and tree-based regression techniques[11]. In 2018, a group of Australian authors[12] used LASSO model to describe fully automated loss reserving on the example of non-material damages in motor third party liability insurance. In 2015, a group of Turkish authors[13] contributed to setting a system for prevention of frauds in health insurance by using machine learning method.

So far, the domestic authors have not explored the use of machine learning in Serbian insurance business.

[10] Henckaerts, R., Cote, M.-P., Antonio, K. and Verbelen, R. (2019). *Boosting Insights in Insurance Tariff Plans with Tree-based Machine Learning*, Cornell University arXiv:1904.10890, New York, USA

[11] Wuthrich, M. (2016). Machine Learning in Individual Claims Reserving, *Swiss Finance Institute Research Paper Series No. 16-67*, Geneva, Swiss

[12] McGuire, G., Taylor, G. and Miller, H. (2018). Self-assembling Insurance Claim Models Using Regularized Regression and Machine Learning, *http://dx.doi.org/10.2139/ssrn.3241906*, Sydney, Australia

[13] Kose, I., Gokturk, M. and Kilic, K. (2015). An Interactive Machine-learning-based Electronic Fraud and Abuse Detection System in Healthcare Insurance, *Applied Soft Computing* 36, pp. 283-299

III. Concept

1. Problem-Solving with Machine Learning

A large number of problems encountered in practice can be reduced to some kind of a function that depends on a number of parameters. For example, real estate prices depend on the area, number of rooms, location, year of construction, type of heating, floor, etc. If the software somehow manages to connect all that information or just the information it chooses so it can determine the price of the new property, the software is considered to have "learned" to do the pricing. In machine learning, one does not need to know anything about the method that software uses to determine the function of data interdependence. The role of a human is to provide sufficient information from the past e.g. about real estate sold, whereas the role of the software is to somehow connect that data.

However, it is important to understand the principle according to which software works. One of the simpler methods is to first try to establish a simplified property price function with, for example, 3 variables, as follows:

$$\text{price}(x_1,x_2,x_3,x_4) = \text{area} * x_1 + \text{location} * x_2 + \text{age} * x_3 + x_4$$

where x_1-x_4 are so-called weighting factors selected by the software to obtain the optimal solution, i.e. to obtain the smallest error. In the beginning, it can assign each weighting factor a value of 1 and release any examples of the sold real property it has available. Of course, the prices obtained through this feature will be much different from the original ones.
When squaring errors for all existing data on the sales of real estate, a total error is obtained, which can be presented as follows:

$$E = \sum (\text{actual\_price} - \text{price}(x_1,x_2,x_3,x_4))^2$$

The next step is to change the weighting factors so as to reduce the total error to a minimum. If the total error could be made equal to zero, this would mean that the function is perfect and that all examples from the past can be fully described by the given function and the selected weighting factors, that is, the price at which the next property will be sold can be predicted with high probability, based on the mentioned parameters (surface, location and age). Naturally, weighting factors are not changed by random guessing, but by minimizing the total error function with the use of partial derivatives for each weighting factor:

$$\frac{\partial E}{\partial x}=0$$

for $x_1,..,x_4$.

In practice, standard machine learning software does it all on its own, trying out interdependencies of variables that are much more complicated than the linear function given in the example, but the principle is similar.

2. Features

Although the concept of machine learning is quite simple, it takes considerable experience to successfully apply it to a particular problem in practice. Researches have shown that machine learning software configured by an experienced developer provides much better data interdependence than the attempts of an expert in a particular field who uses his knowledge and experience to formulate the rules.

Software provides a function that is a black box for the person who configured it, but even though one does not understand the interdependencies between the data, one can show that the results provided by the software are correct by using examples.

Machine learning works only when in reality there is a connection between the data. If the software includes the information about the books that the property owner has read and about the price for which the property was sold, there is no chance in the world to use the books to determine the price of property. The best results are obtained when machine learning is engaged in solving the problems that could be solved by humans, because machine learning software solves them in a much faster and better way.

3. Application of Machine Learning

In practice, machine learning is an iterative process with the following steps:

- Providing relevant data to solve a particular problem
- Preparing the data for analysis by machine learning with the aim to process only good-quality and reliable data
- Selecting appropriate machine learning algorithm
- Training the algorithm, which may be supervised, unsupervised and reinforced, which is necessary for the creation of a good model
- Evaluating the model to select the algorithm with the best performances in relation to a particular problem
- Distributing the created model to the users in the form of application
- Problem-solving by users based on their own data which the model has not seen before
- Assessing the validity of problem solution and returning to the beginning of the process until satisfactory solution is reached.

4. Algorithms[14]

Machine learning algorithms differ from standard algorithms in information technology, because in machine learning, the data create model rather than starting the algorithm with data input. The main advantage of this approach is that it eliminates biases and misconceptions from the model. Choosing the right algorithm is not an easy task and it takes an extensive experience to make a choice that is good enough to produce a model suited to the specific problem. Most commonly, algorithms are written in one of the following programming languages: Java, Python, and R.

The most interesting machine learning algorithms are:

- Linear regression - this algorithm is mostly used in machine learning. These algorithms are used for statistical analyses by managing to establish links between data. Algorithms using regression can quantify the strength of the correlation between variables in a given dataset, and based on historical data predict the values of variables in the future.
- Clustering - objects with similar properties are grouped into clusters so that all the objects in one cluster are more similar to each other than the objects from other clusters. Algorithm firstly recognizes the object parameters and based on the parameters subsequently classifies the objects.
- Decision Tree – A flowchart-like tree structure is used to display decision results. Each end node of a tree represents a possible outcome of the algorithm, while branches come out of the decision nodes depending on the value of the parameter in the node.

In addition to the above, used are instance-based algorithms, regularization, rule-based machine learning, neural networks, etc.

5. Preconditions for Intensive Development of Machine Learning Application

Although the main principles of machine learning were developed more than fifty years ago, the application in practice has been particularly intensified in recent years, because it was not until then that the necessary preconditions were met.

Modern computer processors have now become able to deal with a large amount of data and still run fast enough. Data warehousing costs have dramatically dropped. Relatively simple possibilities were created enabling the connection of a large number of computers into clusters that can analyse large amounts of data at a satisfactory speed. Due to general digitalisation, many different data (meteorological, medical, social networks, etc.) have become commercially available through cloud services and APIs. Through open source communities (e.g.

[14] Hurwitz, J. and Kirsch, D. (2018). *Machine Learning for Dummies*, IBM Limited Edition, John Wiley & Son, New York, USA

Google's TensorFlow), machine learning algorithms have become free and easily accessible to those interested.

Owing to the fulfilment of these prerequisites, the insurance industry was not left behind in the intensive application of machine learning.

IV. Application of Machine Learning in Insurance

Insurance industries worldwide have already implemented numerous projects that were based on machine learning.

The analysis of Big Data Analytics conducted by the European Insurance and Occupational Pensions Authority (EIOPA)[15] has shown that in motor and health insurance, about one third of European insurance companies use machine learning in their business. A total of 222 insurance undertakings and intermediaries from 28 jurisdictions have participated in this thematic review. Machine learning methods and software are already actively used by 31% of companies, and another 24% are at a proof of concept stage. These advanced methods enable accurate assessments of different trends with or without human intervention, increasing the efficiency of decision-making and thus reducing operational costs.

The analysis conducted by EIOPA has shown that traditional data sources (demographic data, exposure data and claims data) are increasingly combined with machine learning technology, rather than with new sources (like telematics data, genetic data, credit card data). The most important result of the use of traditional data in a new manner is that it enables the development of products better tailored to individual insureds and better risk assessment. In addition, insurers increasingly use the data outsourced from third-party data vendors to calculate credit scores, driving scores, claims scores, etc.

1. Application of Machine Learning across Insurance Industry

The EIOPA study has shown that machine learning may be used in the following areas of insurance [16]:

• Development of new products – introduction of usage-based products (e.g. driving of a vehicle), products tailored to the needs of individual insured person, new types of insurance (e.g. cyber insurance), etc.

• Pricing and underwriting – enhanced risk assessment, introduction of new, additional elements to policy pricing, predictive models for claims, price optimisation, policy cancellation modelling, etc.

• Sales – automated advice, eliminating intermediaries from policy selling, sophisticated Customer Relationship Management System, increased number of interactions with insureds, etc.

• Post-sale services and assistance – smart applications of mobile devices, customer

[15] EIOPA (2019). Big Data Analytics in Motor in Health Insurance: A Thematic Review, *www.eiopa.europa.eu*

[16] EIOPA (2019). Big Data Analytics in Motor in Health Insurance: A Thematic Review, *www.eiopa.europa.eu*

service available 24/7, chatbots, automatic warnings of natural hazards such as floods, storms, etc.
• Claims management – advanced analytics in the prevention of insurance frauds, verification of photographs as a support to loss assessment on vehicles, automated invoice verification e.g. from repair shops and their payment, etc.

2. Challenges in Machine Learning Implementation in Insurance

The introduction of machine learning to insurance industry may do more harm than good if the following challenges are not addressed:
• Discrimination – given that the learning usually relies on historic data and that machine learning algorithm cannot be prohibited from finding evident connections which, according to the regulations of the European Union, are not allowed for use when defining tariffs (e.g. the information that women live longer than men), it is necessary to eventually verify whether software recommendations are in compliance with regulations.
• Non-transparency of the model – as already explained, the operation of the machine learning software is a black box to customers and may lead to problems in Solvency II regime which requires that the models are transparent and verifiable by auditors.
• Unfair commercial practices – price optimisation may lead the software to include in its calculation not only the risk factors but also the sensitivity factors of particular groups to change in prices or reluctance of particular groups to search the market for a better offer. In addition, the software could find what percentage of the full loss amount the majority of claimants are willing to accept and drop the lawsuit regarding the rest of the amount. Such a practice would not be ethical and could not be considered a fair business relationship with insured persons.
• Abuse of genetics data – since the genetics data may become available through external companies, software may use them for pricing in health or life insurance, which is not in conformity with the EU insurance practice.
• Non-compliance with the GDPR – the companies using the machine learning black box can hardly claim to be compliant with the EU General Data Protection Regulation (GDPR) i.e. to properly handle personal data, which is possibly subject to very high fines in the European Union.
• Compromised data – modern business is increasingly exposed to cyber risks and may lead to a situation where the people operating the machine learning software are not aware that it uses compromised data and draws inadequate conclusions.
• Inadequacy of traditional insurance policies[17] - if a software with machine learning capabilities causes damage, the question may be posed as to who is accountable? Insurance issues are tricky as the potential stakeholders in any AI application range from the algorithm designer, coder and integrator and the owner of the data sets, to the manufacturer of the product using them. Hidden risks of artificial intelligence will force insurers to advance their policies.

[17] Papović, B. (2019) Review of Article Artificial Intelligence – Hidden Risks, source *Insurance Post*, November 2018, pp. 37–38, Insurance Trends 1/2019, pp. 107-108

V. Examples of Applying Machine Learning in Insurance Practice

One of machine learning examples realized in practice and also used by insurance companies is the classification of e-mails into spam or regular mail.

In addition, there are several insurance-specific examples where this technology was applied. According to the 2016 official data[18], the top four insurance companies in the USA use machine learning in different business processes[19], whereas in Serbia, the Association of Serbian Insurers uses machine learning algorithms to combat frauds.

1. State Farm[20]

The biggest insurance company in 2016, State Farm, used machine learning to classify the safe driving of each driver who had their insurance policy and then offered the insurance product for each driver class.

Three years ago, State Farm launched a competition for the most effective solution for driver classification based on the photographs that showed behaviour of traffic participants. Drivers were classified into ten categories: safe driving, texting, operating the radio, talking on the phone, etc. The first place application was the one that utilized machine learning and two neural network models.

2. Liberty Mutual[21]

One of the biggest American insurance companies, Liberty Mutual, founded Solaria Labs, a specialised company dealing with innovations. One of the projects developed by Solaria Labs in 2017 is the development of a portal with an open application programming interface or API (Application Programming Interface). The purpose of the portal is to integrate Solaria Labs' own IT projects with public data, with the aim of developing the traffic safety application based on machine learning.

In addition, they have developed a mobile app which assists the drivers who had a car crash to quickly assess vehicle damage using a cellphone camera. The training set of machine learning application consisted of thousands of traffic accident images paired with the data on the repair costs of the photographed vehicle.

[18] National Association of Insurance Commissioners website *www.naic.org*

[19] Sennaar, K. (2019). How America's Top 4 Insurance Companies are Using Machine Learning, Emerj Artificial Intelligence Research, *http://emerj.com*, Boston, USA

[20] *www.statefarm.com*

[21] *www.libertymutual.com*

3. Allstate[22]

Insurance company Allstate has developed a virtual assistant, Chat-bot ABIE (Allstate Business Insurance Expert), based on machine learning methods, to help its agents in the sales to corporate clients. Previously, their agents had only been trained in selling homeowners and health insurance, so when the company decided to entrust them with the sale of more complex property insurance products, they required help. ABIE provided agents with a step-by-step guide in English for applying tariffs, pricing, and preparing a variety of corporate insurance products. Since ABIE provided quality assistance, agents benefited from its services on a monthly basis, in about 25,000 cases.

4. Progressive[23]

Major American insurance company, Progressive, leverages machine learning algorithms for predictive analytics to study the data on client drivers with the aim to achieve a better understanding of market trends and possibility to further develop motor insurance products. Their telematics app, Snapshot, collected 20 billion kilometres of driving data in 2016.

5. Association of Serbian Insurers[24]

Almost all major Serbian insurance companies have the organizational units established for fraud prevention, which are more or less successful in combating frauds. In order to successfully combat fraudsters in the field of motor insurance, in 2015, the Association of Serbian Insurers provided insurance companies with a powerful tool to combat frauds. FROPS (Fraud Risk Operational Performance Solution) of the UK-based company Salviol[25], software for fraud prevention, is an analytical tool used in insurance and other financial sectors. The main objective of FROPS is to collect, compare, research and analyse large amounts of data. It looks for anomalies, discrepancies or inconsistencies in the data in order to detect fraudulent actions which lead to loss of revenues. FROPS analyses the widest range of information to provide the most efficient analytical environment with maximum precision of key fraud indicators. It indexes the data from which it calculates the risk of fraud and operates independently from other programming environments. This solution uses predictive analytics and machine learning to identify new types of insurance fraud.

The key indicators of fraud are the damage parameters that indicate a high likelihood of fraudulent actions. They represent a critical point for fraud detection and prevention systems. Proper combination of these indicators narrows down

[22] *www.allstate.com*

[23] *www.progressive.com*

[24] *www.uos.rs*

[25] *www.salviol.com*

the set of potentially fraudulent claims. In further control and analysis, the Anti-Fraud Department focuses on this set, which increases its effectiveness. FROPS recognizes the unstructured data, text files, scanned documents, etc. and enables their search, analysis and categorization. The data thus prepared give the analyst the insight necessary for the investigation process.

In addition, FROPS utilizes quantitative technique to analyse social networks combining the organisational theory with mathematical models. Based on these algorithms, the analyst can better understand the dynamics of groups, networks and organizations. It can identify persons or organization that hides information, monitor and analyse how networks evolve over time, and very quickly identify important characteristics of the analysed group.

VI. Conclusion

Numerous machine-learning projects to combat frauds, define tariffs, settle claims, provide support to customers and agents, have already been implemented in insurance industry worldwide, particularly in health and motor insurance.

This paper aims to shed light on the application of machine learning in insurance and draw attention to the challenges of machine learning, and thus encourage Serbian insurance companies to use machine learning techniques with the aim to advance and modernize their internal business processes.

In view of numerous advantages insurance industry can expect from the introduction of modern technologies described in this paper and supported by the examples from foreign and domestic practice, in the coming years, it is expected that Serbian insurance companies will benefit from a more extensive use of machine learning.

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Translated by: ***Zorica Simović***