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Chapter 6: Artificial intelligence and machine learning applications in underwriting, fraud detection, and risk assessment

6.1. Introduction

The discipline of underwriting is generally fairly conservative, but because insurers are trying to squeeze more information and value out of increasingly abundant data sources, increasing interest has been applied to the use of Artificial Intelligence and Machine Learning technologies in underwriting. These discussions are primarily concentrated in Personal Lines where the large volume of homogeneous data can enable AI and ML to produce results rapidly, but as more data is collected in Small and Medium-sized Enterprises, Delegated Authority Schemes, and Commercial businesses, this technology will inevitably be applied more widely. Insurers have recognized that they are sitting on a vast data mountain, leveraging them through the use of AI and ML technologies to squeeze the last ounce of value and insight from this data. These applications run the whole gambit from the direct use of AI and ML within underwriting models to the deployment of AI-driven tools that assist underwriters in their operations. The workflow across personal, SME, and commercial underwriting is changing based on this technology adoption. AI is complementing and augmenting underwriting decisions through predictive scoring and new insights distilled or sourced via AI (Rahman et al., 2023; Kim et al., 2024; Patel et al., 2024).

While the use of AI and ML in risk selection is the original driver for its adoption, the technology is impacting other areas of underwriting workflow. Be it through automating key reports or general tasking, collating information across sources and enabling ratemaking to be completed rapidly, improving the general experience and workflow users experience, or enabling the support of less sophisticated users through chatting interfaces. AI and ML are having a sustained impact on the underwriting domain. Risk selection, file assessment, business classification, portfolio review, business optimization, and service or partner selection are only a small selection of the many applications across the underwriting discipline (Singh et al., 2023; Silva et al., 2025).

6.1.1. Background and Context

Many companies across diverse industries invest considerable resources in risk assessment and management. While an intricate part of the decision-making process, risk assessment is often time-consuming, cumbersome, error-prone, and subjective.

Fig 6 . 1 : AI-Powered Risk Assessment: Transforming Industries

However, digitization and the explosion of big data have created opportunities to improve traditional risk assessment. Fast-evolving AI and machine learning technologies analyze vast data sources at affordable costs. A growing number of organizations employ these technologies in risk assessment, gaining efficiency and accuracy compared to traditional processes. Increased automation improves decision-making and reduces reliance on inconsistent risk assessment by individuals and teams. This book focuses on the deployment of AI and machine learning technologies in risk assessment for three activities: underwriting, fraud detection, and overall risk assessment to inform business objectives or enterprise risk management. It illustrates the promise of these technologies to transform risk assessment decision-making while also raising several challenges and concerns. Subsequently, subsequent chapters examine one of the three activities in greater detail. The underwriting process has remained relatively unchanged for several decades. Demand for easier, quicker access to insurance information coupled with emerging risks has compelled organizations to explore advanced solutions to optimize underwriting. This chapter shows how insurers are leveraging AI and machine learning-driven solutions to improve the underwriting process in several distinct areas, from automating mundane rules-based logging and data extraction processes to improving prediction capabilities for prospective new clients or predicting the likelihood of early customer attrition, through to enhancing fraud detection functions.

6.2. Overview of Underwriting

Underwriting is the detailed financial assessment and examination performed by insurance companies to gather information on the risk proposal so that they can decide whether to accept or deny the case. The level of risk associated with each applicant determines the cost of coverage and premiums. This information is passed on to the agents who guide the client to the pricing related to the risk levels. Underwriting is the art of balancing the underlying risk of an applicant with what it costs to insure that risk correctly. An accurate underwriting process will directly contribute to an insurance company's earnings and the actual risk associated with the business of the company.

Currently, insurance companies are facing several challenges that undermine their business activities. The underwriting sector is currently inundated with high data inflow and strict regulatory pressures which in turn leads to a high pressure on the underwriting professionals. Further, the current underwriting process is cumbersome and time-consuming affecting customer engagement. Underwriting currently receives insufficient funding, adheres to old-school processes, and contains outdated tools. However, all these challenges can be overcome with the implementation of AI and machine learning technologies. The incorporation of AI models in underwriting can process huge amounts of data and make accurate predictions in real-time without compromising on the quality. Additionally, AI solutions can help with enabling simplified decision-making, effective fraud detection, improving risk assessment, and using data to better determine the appropriate price for the risk. Furthermore, AI solutions can also assist the underwriting teams with more automated data entry and simpler methods to interface with various data sources.

6.2.1. Definition and Importance

In insurance, underwriting is the process of assessing the risk profile of applicants to determine the appropriate amount of premium for the risk or whether insurance should be provided at all. It is, therefore, a critical area within the business of insurance and for any other insurance-related functions such as pricing, risk assessment, and capital allocation. The dictionary definition of the word underwrite is to give an undertaking that the liability for an action, or for the loss, destruction, or depreciation of something will be assumed and to establish a price for a security issue in the stock market. In finance and insurance, underwriting refers to the process by which an underwriter assesses, at a given premium, the risk of an individual application of insurance and decides whether the risk is acceptable to offer insurance coverage. This practice is also referred to as risk analysis in the area of risk management but is, in fact, the same as underwriting in insurance.

In the underwriting process, insurers review the information gathered from applicants; analyze the creditworthiness, risk profile, and capabilities of applicants over the short and long term; and if necessary, collect additional information and ask for the assistance of experts in certain cases. In some more complex lines of insurance, the underwriter may also consult make use of models, tools, and actuaries to draw conclusions and make decisions about particular large or unusual risks. In making risk assessments and underwriting decisions, insurers use a variety of quantitative and qualitative techniques, reflecting the multi-faceted nature of risk.

6.2.2. Traditional Underwriting Processes

The underwriting process assesses and quantifies risks associated with insuring a policyholder, who may submit up to 1,000 pages to an insurance company for underwriting at policy inception. Underwriting has existed since merchants in 15th century London began requiring protection against loss to their ships at sea. Merchants would pay a large amount of money to the investors for insurance protection in the event of loss of the vessel or cargo. The merchant would be provided a receipt from the investors who agreed to pay in case of loss. But peril could only exist with the ship away from the protection of a port. Investors had to wait for weeks after loss of the vessel to find out if they had a loss. Loss data plus mitigation actions taken on similar vessels can determine the likelihood of loss and evaluate the risk. Because settlements took a long time, investors began endorsing the receipt and putting a limit on their liability. Originally, it was a private matter requiring no official stamp. Investors began putting their names on the receipts as the practice of “underwriting” became common.

The underwriting process analyzes risk characteristics to ensure each insured pays a proportionate share of overall claims costs. Assigning each insured a unique and meticulous underwriting strategy determines the necessary risk mitigation actions to ensure reliability and performs a financial magnitude analysis that examines the risk versus reward on a portfolio of insureds. These steps together guide the use of data to drive the underwriting process. To illustrate, a high-performing company could use its resources in several ways, such as recruiting additional agents or reinsurers or entering new markets. The resources would be better spent buying a data-driven underwriting system or responsive reinsurance for capacity relief.

6.3. Artificial Intelligence in Underwriting

Several new technologies, trends are emerging across the financial services and fintech landscapes. The financial services industry is overwhelmed with uncertainty and economic volatility. Growth propensities are deeply impacted around the world due to rising interest rates, declining loan origination volumes, and the fallout of major banking systems caught up in interest rate pressures. Be it a startup or an established financial institution, all are seeking new ways to innovate and balance and adapt their business models to meeting customer needs post-pandemic.

Underwriting is a systematic process and significant components of the credit decision-making process undertaken by insurance, banking, and financial service companies, including their subsidiaries and affiliates. With the use of sophisticated risk models, all factors that make an applicant eligible for availing of insurance policies, or loans are identified. However, there is no uniform process followed for underwriting. Different businesses follow different methods to assess the risks associated with the loan or insurance migration.

Improving data transparency with better approaches to underwriting and risk pricing is seen as a key trend within financial services and financiers. The demand for such improvements is being driven by customer expectation for lower pricing, improving technology, and strong competition among lenders and insurers, typically encouraged by low entry barriers and the increasing availability of policies and loan products. Early-stage technologies, beyond traditional credit scores and borrower financial performance data, are presenting much more holistic views of the risks associated with borrowers and allowing for a pricing decision to be tailored to each loan or policy in order to optimize and guarantee profit for lenders and insurers.

6.3.1. AI Technologies Used

In this section, we will consider the AI technologies that are being used in underwriting; to be more specific, we will expound on the different AI technologies that are used for underwriting in various areas – life and health insurance, property and casualty insurance, commercial insurance, and specialty insurance. We begin with general technologies, focusing specifically on Natural Language Processing; Data Processing and Algorithms; Predictive Modeling; Decision Support and Expert Systems; and Hybrid Decision Support and Expert Systems.

Natural Language Processing is capable of analyzing unstructured data in the form of text. Such data is available in written form in large volumes, e.g., in the practitioner domain such text is available in annual reports, earnings call transcripts, company filings, industry reports, news articles, and so on. Such text contains a lot of nuanced information about key industry, financial, and operational factors that may affect the underwriting decision. To utilize this written data efficiently, NLP can be used by an expert system, which is capable of making decisions upon analyzing specific underwriting factors, e.g., industry sector and sub-sector, company size, history of adverse selection, and so on. Alternatively, the NLP can also be used as input to risk models, which predict a company's future risk profiles, a process that is hoped to provide more accurate results compared to the conventional rating factors approach.

Data processing and algorithms in underwriting use unique data such as credit card transactions, health record timestamps, patterns of digital sharing and influences between social network users, and e-mail message patterns that help companies accurately price risk. Predictive modeling on heterogeneous data structures, which include short term, continuous, discrete, high-dimensional, and relational-valued response variables related to potential future insured losses allows insurance companies to improve pricing accuracy on various fronts, including predictive performance, derivative pricing ability, model specificity, sensitivity, and pricing control.

6.3.2. Benefits of AI in Underwriting

There are different areas of insurance that can embrace numerous AI characteristics and services to enhance the customer funnel, profit, and operational efficiency. The underwriting procedure, in its essence and framework, consists of the examination and willful acceptance of client risk. The process distinguishes between good risks, average risks, and bad risks. Without a clear idea of how underwriting could be reengineered or further enhanced, it is still great as part of an insurance company. Artificial intelligence algorithms can help to refine the customer funnel by pre-qualifying them in a way that helps to minimize resource efforts later on in the underwriting process. The underwriting funnel is supported by carrier internal structured data and third-party data.

In no event should AI-driven underwriting come into effect autonomously. The final decision will always remain in the hands of an underwriter. The discussion is about using AI-led risk classification for selecting the optimal path for the customer or prospective customer. Artificial Intelligence in its different shapes allows optimization and support through all underwriting processes, including risk estimation, customer targeting, screening, loss prevention, fraud detection, and underwriting positioning. While fraud prevention is more about improving the selection of customers in each funnel, risk assessment, underwriting position, pricing, and contractual terms are about advancing and optimizing the content itself. The support provided by Artificial Intelligence in underwriting will help significantly reduce the dependency on customer interaction and help customers progress in a fully automated and admitted way.

6.3.3. Case Studies

This section uses four case studies to demonstrate how data science and AI can be used to enhance the underwriting function from the initial proposal stage to policy placement. The studies encompass predictive modeling, NLP, reinforcement learning, and unsupervised learning.

The first case study details how a leading reinsurance company was able to improve the accuracy of property loss models through the implementation of a parameter optimization process combining reinforcement learning and gradient-free derivative optimization techniques. The second case study describes how a homeowner's insurance company was able to reduce application fraud and improve loss estimation accuracy through the use of NLP techniques to parse, classify, and derive meaning from numerous documents.

The third case study details how a large property casualty insurance company was able to reduce fallout from the underwriting case review process through unsupervised learning techniques. The fourth case study describes how a large property cybersecurity insurance company was able to enhance transition learning from pipeline service improvements to underwriting changes through the use of machine learning techniques.

All the case study implementations demonstrate that building a Data Science center of excellence and Data Science guild with dedicated resources, including executive sponsorship, specialized data and ML engineers, data quality processes with feedback loops, and a model management and validation framework, is key to advancing the underwriting organization's business objectives through the use of AI.

6.4. Machine Learning Techniques in Underwriting

Data is then recorded in data warehouses; however, before performing any analysis, data cleaning must be done. This data cleaning could be carried out using Machine Learning techniques inside and outside the insurance sector. A challenge is the lack of standardized formats for data in insurance domains, and usually these data are unstructured. An analysis of the above products can be useful to identify input parameters and filters used. However, there are not too many works found that preceded pre-processing, filtering, selections of input parameters, and generating structured datasets after understanding the business clearly. These machine learning tasks may come under pre-processing of data.

Once this data is stored, underwriting and fraud are automated using machine learning tools. Machine Learning techniques are also used to optimize models created in traditional underwriting using claims data for existing customers. These techniques optimize costs and select hazarding customers, coordinating customer and company interests. These techniques are also used to validate complex business models with new various inputs. Automated systems are developed using Machine Learning architecture where the agent is the computer and the state is software driven by data. Also rule-based systems have been deployed as a second step or a replacement product. Basic flow is from data to model to rules to decisions or actions.

An agent-based model provides the entire architecture governed by business processes displayed in UML, engaging theory and decision products and knows on the functional operation, capacity, type, amount, volume, size, and timing of input for a process. The capability of an entity to process transactions relies on the lifecycle of the business, and each model deploys the lifecycle appropriately. While entity-based and OM-based frameworks provide single product development views, standardization reduces complexity and enhances the robustness of machine learning underwriting processes.

6.4.1. Supervised Learning

Many financial and business processes can be modeled as decision problems based on historical records. For example, an investor may want to predict the yield of an equity index, a bank may want to determine the probability of default of clients of its credit portfolio, and an insurance company wants to estimate the probability that a home will suffer losses covered by its policy. In this context, every input corresponds to a different decision made by a human agent, and the objective is to identify the relationship between this input, normally consisting of multiple features, and the decision output to be predicted. In recent years, an increasing number of decision-based data for important operations in the bank and insurance industry have become available, enabling the application of machine learning classification algorithms. In addition, these algorithms have the advantages of requiring low computational power and being flexible in modeling the relationship between the predictors and outputs.

Two examples of decision problems at banks are the binary problem of predicting the probability of default of a credit portfolio and the categorical problem of detecting if an incoming transaction is fraudulent after it has occurred. In the first case, information from clients that defaulted and clients that did not default is known in a historical training dataset, and a prediction must be made for a future client that is currently new to the bank. In the second case, a historical dataset regarding the transactions flagged as fraudulent and those that are not flagged is available, and the prediction must be made in real time and is verified later.

6.4.2. Unsupervised Learning

The main function of Unsupervised Learning is to identify relationships between data variables by groups or clusters without training data, such as hidden features, data distributions, and intrinsic patterns, to extract useful information regarding the dataset. Clustering and Association Analysis are commonly used in Unsupervised Learning, and their common models include Expectation Maximization, k-means, k-mode, Hierarchical algorithms, Gaussian mixture models, Autoencoders, Self-organizing maps, and so on. The clusters can represent something meaningful in the presence of a label or can help build a predictive model. Moreover, there are some indicators to help understand how good their clustering is, and some are used with concept to visualize those data. The results of Unsupervised Learning can be used as customer segments important for Cross-selling or Up-selling, which helps design more personalized services or products.

The raw data comes from various sources that register information regarding a relevant customer, including financial information, loss history, demographics and interests, and policy and risk characteristics. The insight from the visible structure is used to calculate useful statistics, such as the frequency of customer types or loss rates by customer type, which can be used to calculate the Loss Cost and Loss Ratio applicable to each customer segment. Clustering in Unsupervised Learning is commonly used to find customer segments with similar interests or characteristics to help price the products more accurately, market products to customers effectively, or provide services more efficiently by defining suitable marketing strategies for each customer segment. There are some applications that employ Unsupervised Learning for tasks.

6.4.3. Reinforcement Learning

An alternative approach is reinforcement learning, which explicitly calculates the cost and benefit of an action to produce a reward, enabling a sequence of actions to maximize the rewards. For example, reinforcement learning is widely used for model-free control because terms such as feature extraction or control designs do not have to specify the task at the beginning. Reinforcement learning can learn the task by interacting with the environment and adapting the policy. Reinforcement learning can also minimize the need for supervision when a sequence of decisions/steps is crucial. All that is required is for the agent to see the impact of its action over time. When RL was first introduced, the policy learned was too simplistic to produce interesting, long-range, difficult problems. For example, reinforcement has been applied at the feature level for low-level perception tasks like facial recognition, hiding notes, and slot-filling conversation.

Reinforcement learning can be treated as a linear multiplier on top of the unsupervised feature representation. Such applications have not been applied at the top level where deep multilayer networks have been trained via back-propagation relied on very restrictive independence assumptions. When reinforcement learning is used at the top level, a teacher provides the reward signals to the top network. This information is then propagated down through the feature channels. Features that enhance performance at the top are amplified, and features that have adverse effects are suppressed. In this chapter, we will deal with various applications of reinforcement learning. We will also present a few case studies. The deep reinforcement learning algorithm presents a great framework for the human brain due to common concepts such as layers and signals. Since DRL is inspired by the human reinforcement learning model, this can be the ultimate advanced concept for human modeling and understanding.

6.5. Fraud Detection in Insurance

Unfortunately, insurance fraud is very common and is often unnoticed for a long period, until its consequences are gigantic and then the insurance companies attempt some coercive means to recover their financial losses. Therefore, fraud detection in insurance is an important area receiving great deal of attention. It can be solved as a solution of classification which creates models for two classes of legitimate and fraudulent cases by evaluating the available attributes. Generally, insurance claims, transactions, applications, policies and brokers are the most concerning areas of insurance fraud. The early identification of fraud is a significant problem in the insurance industry which can avoid huge losses. Insurers must take into account specific actions which lead to some risks and concerns because some customers take to unethical acts since they are motivated by some reasons. The factors triggering motivation may include aim to physically harm and/or damage a third party; expectation to gain more from an illegal act than from an ongoing legal policy; perception of being able to obtain some financial gain from the collateral damage and the sense of feeling little or no guilt about the decision. To avoid fraudulent acts insurance companies must establish some preventive and investigative detection systems both with desktop tasks focused on the business field and with IT systems dealing with predictive detection. The facts concerning the motivation along with detection systems lead to the conclusion that fraud detection involves the encouragement of ethical behavior, the evaluation of the behavior not only on a business sense but also on a moral point of view, the design and recommendation of adequate policies, and finally, the detection of suspicious behavior, possibly by means of data mining and expert systems. These types of systems, if adequate and implemented in a well-planned way, can guarantee a high degree of operational efficiency with a minor investment.

6.5.1. Understanding Insurance Fraud

Insurance fraud is defined as a fault act committed against or in the insurance industry, unlike other victims, that is performed as an intentional breach of a legal duty or for an unlawful purpose and results in the perpetrator being compensated and the insurance company or society losing. Therefore, faced with the fraudulent claims that occur frequently around the world during the past years, the insurance industry has implemented different methods for fraud detection, starting with non-automated systems of dubious success that rely on various ratio technology application. However, it is now recognized that the assistance of Artificial Intelligence and Machine Learning techniques in the fraud prevention process can be an influential guide in reducing the fraud losses. These techniques can discover complex patterns in the dataset with individual features. Insurance fraud schemes include provision of false or misleading information on registration or claims processing to take advantages of the insurance policy. It may involve everything from employing unqualified specialists to avoid taking care of a problem and then submitting false claims against the employer's liability insurance to obtain medical insurance to commit fraud, which may be also be an accomplice with the injured party, using one of the alibis previously mentioned, buying a probability life insurance policy and then dying in a plane crash or car accident for lack of medication or using, during a trip, a travel insurance policy with medical expenses and to commit fraud on these policies, which are usually also quite cheap. Many other are the types of insurance fraud schemes found these days.

Fig 6 . 2 : Fighting Fraud: AI in the Insurance Industry

6.5.2. Types of Fraudulent Activities

The insurance business offers a lucrative lure for greedy individuals who may tend to deviate from the right path and embezzle money from insurance companies illegally. The entire insurance business is governed by laws, rules and regulations. Insurance frauds fall into one of three categories of criminal behavior. These are: providing false or misleading statements, providing information for material fact, or being involved in more diversion. The growth of fraudulent practices not only affects the insurers but also affects society at large. The costs incurred by the insurers to compensate the fraudulent claims are transferred to the non-fraudulent policyholders by way of increased premium. Insurance frauds have multiple objectives with a measurable concern being revenue collection and other personal materialistic benefits. Fraud may also result because of greed for material possessions and excitement of living outside of the law. Specific reasons for engaging in insurance fraud depend on socio-economic status and the position in life cycle. Financial difficulties, gambling addiction, and potential for financial gain may be a motivation for some people while other reasons may be for more passive individuals who perceive insurance fraud to be a "victimless" crime with no one else hurt.

Insurance fraud is present in all lines of insurance – whether property, health, life or others. The most common health insurance fraud remains false pretenses for psychological and dietary services. Whereas general insurance fraud tends to be against car, property damage and petty theft. Different types of crime to be committed in the insurance field may be – fiery losses to a domicile, vehicle and asset theft, random arson, and Crooked House. To suspect without proof makes the insurers seem more like accomplices than professionals seeking to protect the legitimate policyholders against sub-customers, thieves and disingenuous agents.

6.6. AI and Machine Learning in Fraud Detection

Fraud detection is perhaps the oldest and most widespread application of machine learning. AI is mostly applied to processes that are of high volume and are done repeatedly, traversing a route through different departments or systems, either taxed by processes of a large number of external actors or a limited number of internal actors. All of them doing the same activities, without due care in identifying anomalous behavior. Companies across the globe have started implementing various AI capabilities to capture real time data, analyze comprehensive data sets, and partner with vendors that can leverage predictive analytics and adaptive learning to offer better solutions and response times.

Predictive Analytics offer solutions such as improved screening of client risk levels for new and existing accounts, better forecasting of potential shortfalls, efficiencies in review processes through predictive risk modeling, forward looking risk analytics, identification of high risk clients and enhanced decision making support tools, thereby leading to reduction in false positives and negatives. PA assesses the risk of loss in specific areas and the potential value of improving those areas and quantifies the costs and benefits of solutions. These risk areas would include Merchant Risk, Customer Risk, Distribution Channel Risk, Key risk indicators, among many other categories.

Insights from predictive models can help fraud prevention associates better monitor those accounts that show fraudulent behavioral patterns. Challenges are becoming more in-depth as it becomes more difficult for criminals to commit fraud against any system without being detected. Today’s technologies are capable of capturing more data, and with deeper and more robust analytics capabilities, PA can create more predictive models. But the hurdle is to develop better monitoring processes that will allow your review associates to work most efficiently.

6.6.1. Predictive Analytics

Predictive analytics involves the use of predictive models and machine learning techniques for predicting and mitigating undesirable events or conditions. The classic example of predictive analytics is forecasting, where, based on historical patterns and assumptions, predictions are made for a future unknown, usually using periodic time series data. For the case where there is a historical encrypted database with transaction records but with no transactions in the future, predictive modeling is performed. This involves using the set of historical transaction records to train a predictive model from previously understood historical patterns. The trained predictive model can then be used to evaluate future transactions and help identify for further review any that are predicted to be fraudulent and/or risky.

Predictive modeling is powerful but has a number of limitations. One limitation is that conditions must stay approximately the same or be the same as those that existed during the model training process. For example, if there is economic turmoil or there are significant changes in the organization or external intelligence data, then predictions are likely to be wrong. In these cases, new models can be built. This is a pain point for organizations, as it requires expert resources and loading the system with potentially inaccurate and risky models. Because of these caveats, predictive analytics is best used in conjunction with the other techniques discussed. Furthermore, predictive model training can be resource-intensive.

6.6.2. Anomaly Detection

Model-based mechanisms have been used for anomaly detection since the 1960s, where a model is used to characterize normal transactions in detail. Such models serve as a basis of the detection of new instances. However, if the model of normal transactions is not adequate, the detection fails. And any change of the normal behavior mandates a model update. The main challenge of using model-based approaches for fraud detection is the fact that the concept of anomalous behavior evolves and newly constructed models based on voting classifiers normally are not fully adequate.

The first step is to construct a model for normal transactions that adequately fits the dataset, leading to an issue unrelated to the detection process itself, but that deals with the process of model construction and may seriously affect the detection process. All available transactions are used to create a model for normal behavior. Moreover, the model is shaped to minimize its complexity. The aim is to create a model that is able to describe as many samples of the dataset as possible, since this will become the model of acceptable behavior. Once the model is built, however, it must be stored to detect transactions in real time while processing the incoming stream of transactions. A penalty is paid since these transactions are not part of the training dataset and huge streams of transactions arriving during production make this dynamic process a challenging one. The issue requires fast responses, as it is unacceptable that fraudulent transactions remain undetected for a substantial amount of time when a model of anomalous fraud is not considered to be fully adequate. This is particularly true in the case of credit card fraud processing, where the consequences of fraudulent transactions can be very high.

Machine Learning offers faster processes where new models of normal transactions can be rapidly constructed using artificial and real data, thus minimizing the time that an inadequate model is used for detecting fraudulent examples. Moreover, ML computational cost also decreases detection time, allowing model construction and prediction in real time, which is paramount in credit card fraud detection.

6.6.3. Real-time Monitoring Systems

In the third approach, mining and analyzing big data streams using machine learning and AI techniques can help in the identification of fraudulent activities as they occur. Thus, based upon the monitoring of changes in behavioral patterns of individuals, the AI system can predict that an insurance claim is linked to a special risk profile of the ostensible claimant. Based on these triggers, the respective claim can be delayed, and further checks performed. These systems have shown a high level of success, but are inherently limited by the fact that they rarely provide additional details about the particular nature of the suspect behavior. Furthermore, it is also possible that money and effort is wasted due to unnecessary investigations triggered by invalid alerts from the system.

While the insurance industry appears to pick up pace with the wider implementation of AI and machine learning applications for the purpose of fraud detection, the underlying algorithms and models sometimes deployed remain simplistic. Only anomaly detection implemented as a hybrid approach combining the deployment of unsupervised AI and machine learning based on non-structured data would allow a deep detection approach by uncovering hidden relationships across all relevant datasets traversing the value chain related to claims that would allow the uncovering of criminal rings. Due to the constant emergence of novel fraud schemes attempting to monetize on various social issues, it seems imperative that the dynamic versions of these algorithms are more widely adopted. A hybrid architecture that attempts to exploit a combination of clustering and evolutionary algorithms for the optimization of the parameters of both models showcases the technical feasibility of such an approach. However, no AI strategy roadmap has yet been published, with a primary focus on such an approach being only examples from the private sector using a very limited input-output design space.

6.7. Risk Assessment in Insurance

Underwriting, premiums determination, risk prevention, and risk settlement rely on a qualified risk assessment. The more accurate the risk assessment, the more effective these operations are. The subject of risk assessment is an individual, a home, a car, a company, etc. The insurance business is group work: the importance of creating a risk assessment lies within risk diversification. Indeed, underwriters analyze risk instances' uniqueness to implement a risk funding or a risk decision that will balance risk diversification and the possibility of suffering claims in excess of the amounts collected. Reinsurers are thus responsible for helping insurers cope with local risk fluctuations. Thereafter, audit committees and rating agencies help ensure diligent company risk and premium management by controlling integrity and transparency.

Implementing an objective risk assessment model is not an easy task. A certain harmonization indeed exists, especially if considering the monopoly situations of certain companies, or the market activity novelty, when compared to a notable mass of other companies, that can rely on historical data and are more mature in terms of the activity's risk profile. Some insurance companies are specialized in certain advantages of individual activity businesses. Others provide insurance policies to cover only most of the totally exposed part, like property, ship, aviation insurers. They never cover operational, general, or other risks of their client.

6.7.1. Importance of Risk Assessment

Risk assessment is a very important part of an insurance company's functioning process. It determines the premiums that are given to potential clients. It is performed by underwriting agents in an insurance firm. Underwriting is very decisive, as it alone decides which applicants are to be turned down or accepted. The underwriting personnel have to consider many factors and regulatory conditions before taking such crucial decisions. The applicant's risk profile plays a major role in underwriting and risk assessment as it helps the underwriters examine if the right premium is decided. Risk assessment is a matter of great importance as the life insurance sector deals with the uncertainties of the lives of people and businesses. Money is an important and sensitive aspect when it comes to insurance, and the amount of risk involved in providing a certain insurance scheme is pondered over ferociously. It is during the risk assessment stage that the company attempts to figure out how much risk it as an insurer is taking and for how much risk is getting compensated. There has to be a correct correlation between the underwriting amount undertaken and the premium amount being charged. If not, the insurance company will suffer huge losses which cannot be rectified in the amortization procedure. That is why underwriting is a sensitive area and so is risk assessment.

6.7.2. Traditional Risk Assessment Methods

Any statistical risk assessment model requires examples of risky and non-reporting claims from which it learns. These claims are used to develop the model. The model is then revised and recalibrated every few years based on more recent claims history. The estimate of the probability of a claim being fraudulent, as produced by the model, will be imperfect, as the model will not accurately depict the probability of fraud or severity of the detected fraud. However, early in its development, a naive model may provide useful information for the underwriter, enabling the detection of more fraudulent claims than without the model. There are two traditional approaches to risk assessment before machine learning. The first is heuristic rules, which is defined from diverse practical experiences, while second is logistic regression, which is statistical modeling technology. With heuristic rules, risk assessment is performed according to practical experience. Various rules have been defined over time. Examples of these rules are that slow speed means less risk, and bright color highly visible means more risk. Generally, heuristic rules mostly consist of judgment based on practical experience concerning risk assessment.

Despite their wide applications, heuristic rules have several limitations such as criteria limitations and risk characteristics quantitative limitations. Due to such limitations, heuristic rules are not considered to be very effective at risk assessment. While there are other statistically predictive methods besides heuristic rules, these other methods may not be as good as logistic regression in prediction accuracy. A logistic regression model calculates the log of the odds of an event occurring and relates it to a linear combination of predictors by means of a logistic function. The terms "logistic regression" and "logit" are often used interchangeably to refer to this particular kind of model.

6.8. AI Applications in Risk Assessment

It is in the area of risk assessment that we find some of the most established and researched applications of AI, specifically machine learning. In the financial services industry, there are regulations in place that demand that institutions assess, monitor, and manage all the risks they are exposed to or could be exposed to. Credit risk, market risk, liquidity risk, reputational risk, interest rate risk, and operational risk are the types of risks defined by Basel II. On the other hand, there are risks specific to financial services institutions that are more intent-focused and require heightened levels of assessment, vigilance, and monitoring, given their potential for large-scale damage. These risks include money laundering risk, terrorist financing risk, and bribery and corruption risk.

While various enabling technology-based applications of AI/ML have already been discussed up until this point in the text, we now discuss four areas where AI/ML technologies are tangibly helping ESG initiatives, specifically, by helping institutions better assess and model risks to develop more accurate and meaningful insights than were feasible using traditional, manual approaches. To address the problem of data collection and analysis, some third-party solution providers have pulled together databases that cover company strategies, actions, reporting timelines, and quantification of exposure related to key attributes in climate change and other ESG risks, enhancing the quality of the intelligence received by risk assessors. Further, to enable a more intelligent extraction of ESG-related data from publicly available documents, tools are available that leverage AI technologies such as natural language processing and automation using bots to identify and disambiguate relevant datasets.

6.8.1. Data Collection and Analysis

Data Collection and Analysis have always remained a challenge for the risk management professional but AI/ML have facilitated this process. AI/ML has simplified the data gathering process and can integrate internal and external data on the company and the industry. There are many innovative data sources such as captured unstructured data for industry risk and third party reports on the company as well as easy-to-get third-party market reports on various industries that provide qualitative analysis of such industries. Sifting through unstructured data is a daunting but simpler task with AI/ML and we can get more than guesswork on likelihood factors determined by the Five Forces framework play an impact on a particular industry and in what manner. AI/ML can analyze seasoned practitioner views both in terms of publishing and reading/grouping relevant such assessments and narrowing down on the right set around which to aggregate. AI/ML can also keep monitoring various input variables and their relationships in real time thereby assisting in attention to the intervention at the right time.

Integration of all such qualitative data, analyses, changes over time, and data from the company's internal departments: Sales, Finance, Risk Compliance, HR, Legal etc. merits serious thought and work since efficient Internal Control Systems for such Data Collection and Analysis remain the backbone for a solid Risk Assessment Architecture. Data such as External/Input Candle-Sticks, Business Process Flow, Internal monitors, and Events might have to be collectively considered wherever appropriate. Visualization, Gamification and NLP principles using appropriate assistive tech might make the internal data collection from those departments easier to do as a culture as against as a hurdle or a chore and incentivization will take it farther.

6.8.2. Risk Modeling Techniques

Developing risk models is a critical initial step in order to automatically report most of the current risk types and obtain data to be included in what if analysis, risk response strategy and alternative selection, and continuous monitoring. The estimation of the probability that a certain event will occur is an important type of statistical prediction encountered in areas as diverse as economics and medicine. Bayesian methods are a commonly used alternative. Copulas provide a means of constructing multivariate distributions given a set of univariate marginal distributions and quantify the dependence of the random variables. In addition to copulas another possible approach to modeling dependencies is provided by Dynamic Conditional Correlation models, in which the correlation expression is modified. In non Gaussian settings, the limitation is generally due to the difficulty of choosing the appropriate copula function. Like the copula method, vine copulas allow you to create a multivariate distribution from a set of univariate marginal distributions, but they come a more flexible and intuitive structurally.

The risk modeling exercises can be complemented with systems capable of automatically estimating risks and their dependencies in real time. The advantages of this approach are exponential improvement in the quality of risk data and potentially enormous savings in risk model maintenance. In addition to the benefits in terms of speed and cost, automation promises superior accuracy through localization of knowledge in systems and convergence to a best version of the truth and improved self regulation. Operationally, the idea is to continuously observe risk factors that lead towards excessive levels of risk exposures and on the other to update risk estimates and representations as more data and improved versions of estimates and representation become available.

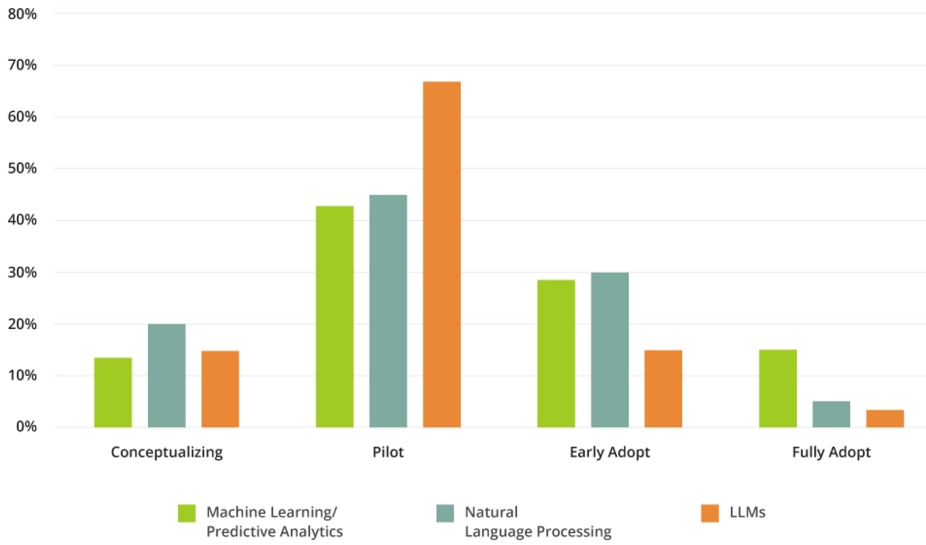

Fig 6 . 3 : AI Risk Assessments in Insurance

6.8.3. Scenario Analysis

Realistic scenario analysis has a special way of explaining the perils confronting an organization. The scenario development process is given particular emphasis in clearly differentiating levels of abstraction, stages of maturity, and overview and detail in the construction of stressful but realistic situations. Gaps in the current literature on scenarios and the IOC are pointed out. Similar omissions regarding realistic scenarios and AI technology applications in military risk assessment are noted. In tackling these problems, techniques drawn from our understanding of combat, expert systems development, technology forecasts, and perspective policy analysis are referenced. Techniques are presented in the context of the broader issue of why intelligence analysis in the West is currently not up to the job, why it is less capable of producing and using realistic scenarios, and how a partnership between decision-makers and forensic and statistical historians could reinvigorate the field.

Scenario-Based AI programs were originally developed to demonstrate the utility of the general area of artificial imagination in support of decision making. They provided decision aids in which an explicit goal-directed subprocess was embedded. The second allocation provided the perspective that, for long-term planning, a reasonable anticipation of future scenarios might be more useful than a probabilistic forecast based on a statistical model. Scenarios are likely to be particularly valuable in studying the options available to countries at points of congruence or of political uncertainty during a crisis period, thereby enabling them to establish within certain scenarios action programs that are broadly directed toward reliable success.

6.9. Conclusion

The financial service and insurance sectors constantly undergo transformations due to the development of new technologies, changing customer expectations, regulatory modifications, and a data-rich environment. Technologies like augmented reality, Blockchain, Internet of Things, Robotic Process Automation, Big Data, Cybersecurity, and Cloud Computing are continually disrupting the sector. This disruption calls for fundamental transformations in business models and surging investments to develop new capabilities. The insurance sector demands radical improvements in efficiency and customer satisfaction and to achieve this goal, they are leaning towards intelligent automation of underwriting, fraud detection, risk management, and claims decision-making processes. The adoption of Artificial Intelligence and Machine Learning technologies in these areas is crucial to optimizing time, effort, costs, decision quality, and stakeholder satisfaction.

On the one hand, intelligent underwriting is crucial to avoid losses and maximize profits, and on the other hand, fraud detection helps the insurance companies to avoid losses and reputational damages with consequent customer discontent. The development of ML models for fraud detection demands the combination of historical labeled data and domain know-how and is the only solution when the volume of data is too prohibitive to be processed with traditional manual techniques. Claim assessment with digital technologies like image processing and intelligent automation optimizes costs and reduces human intervention, thus minimizing fraud risks. Finally, ML algorithms evaluate the risk profile of customers either directly using the behavioral data associated with the company profile or indirectly using graphs built on the customer company profile and social networks. The intelligent automation of these processes improves the business model efficiency, minimizing operational costs and processing time while optimizing decision quality, and positively influencing stakeholder satisfaction.

6.9.1. Summary and Future Outlook

Artificial intelligence (AI) has been adopted by the insurance industry to improve various underwriting processes. Natural language processing is widely used to extract, analyze, and leverage unstructured data. Machine learning is widely used to train sophisticated models for classification and regression using structured data that allows the industry to better detect and prevent fraud. Social network analysis models are also being used to identify fraud rings. A variety of factors, however, have made the use of these AI and machine learning models less prevalent in the industry than in other industries. The costs associated with implementing and managing these models, as well as the extensive regulatory scrutiny the insurance industry is subjected to, have made the industry more cautious. With the vast amount of unstructured and structured data available to the industry, augmentation solutions can help mitigate the issues that have so far hindered the widespread adoption of AI and machine learning in the industry. Augmentation solutions offer business cases that can deliver immediate value along with offshore hosting solutions to quickly and cost-effectively implement the solutions in the long term. With AI and machine learning augmentation solutions, the insurance industry can quickly cash out on the investments made in AI and machine learning.

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