Automated Resolution Pathways in Insurance Claims: Reinforcement Learning Models for Settlement Process Optimisation

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1. Introduction

The growing complexity of the insurance business should enhance the need for innovative tools that can assist the government and the policyholders alike in dealing with insurance. Today, the business has been facing newer challenges regarding ensuring operational accuracy and efficiency. The monumental development in computing techniques and pattern recognition in recent years should bring about change resulting from enhancing the operational efficiency of handling claims, such as accuracy and speed. Among the numerous AI procedures, neural networks stand out as the major candidate for claim settlement.

Armed with the potential to mimic the human thought process, neural networks are a part of the AI revolution. Using them as intelligent tools can ensure cost-effective, consistent decisions that adapt to the varying nature of risks. Neural networks recognize and learn the patterns in databases and perform the process of claim settlement. In the present scenario, both the insurer and the insured who receives the claim are skeptical of today's human settlement process. Hence, there is a need to develop AI-based systems for claim settlement. The importance of setting up the AI-based system leads to the choice of motor insurance data for firing the neurons. The system designed should strengthen the regulator and the consumer of insurance, who come in the form of policyholders.

In today's insurance scenario, motor insurance is considered a key driver of insurance. Claims settlement in the case of motor insurance is increasing day by day. The purpose of the motor insurance policy is to provide compensation in the event of an accident causing damage to a third party. The process followed for handling a claim includes registration of the claim, evaluation of the claim, surveying of damage, repairing of vehicles, issuing bank clearance cheques, and closing the claim. In the motor insurance world, claim settlement happens either through direct settlement of claims by insurance or through litigation settled by the court, which causes many delays. Hence, the need for a new processing system arises that is not error-prone and reduces the time for fulfillment. This paper aims at the AI-based model for a motor claim.

1.1. Background and Significance

Insurance claim settlement has long been a crucial component of the insurance business. The settlement of property and liability insurance claims can be traced back to Babylon and Roman times around 1750 BC and five centuries BC, respectively. Around 454 AD, a legal requirement to register a loss at a local court was described in the Law of the Visigoths. Starting in the late 17th century and throughout the 18th and 19th centuries, the practice of insurance developed considerably given the progression in liability law and financing techniques. By the 20th century, the insurance industry was heavily regulated and had adopted widely accepted practices, such as the principle of utmost good faith, which became a de facto law. Claim settlement through direct negotiations and litigation became best practice for most claim options, and only in 1979 did the ADR become an optional dispute settlement mechanism for insurance claims.

While insurance ratings and underwriting have changed little over time, claim settlement has transformed substantially due to pressure from regulation, which demands an improvement in transparency and accountability, and customer pressure, which demands superior services. The trend will continue unabated, especially in such a digital world where customer care can make or break a customer’s retention. The ongoing trend in digitization and regulatory action in the insurance sector has led to the availability of mountains of unstructured data. An insurance company, being a data-rich industry, is swamped with massive pipelines of transaction data, photographs, and physical proof, making triage and settlement subsequently, if not immediately, difficult. The rise of big data in the insurance sector has changed the claim management process, leading to new solutions that can analyze these vast and unstructured data. The ever-increasing digitization of data and the subsequent compliance risk also drives the need for the development of products that can review this data at speed. Competitive pressures are also shifting the impact of AI on the industry, as more tech-savvy and agile insurers are looking to take advantage of the latest AI breakthroughs to get ahead. Given the low trajectory and mature state of written premium, where the ROI is expected to see a declining CAGR of 6.8%, insurance has turned to deploying data valuation to optimize functional operations, where claims management formed over 69% of the intended analytics-industry task in a survey.

1.2. Research Objectives

With a focus on AI-based optimization in the field of insurance, the goal of this research is to provide solutions for improving the mechanisms of claim settlement. Identifying the present challenges confronted by conventional solutions, this research aims to propose AI-enabled optimization to improve the tedious and time-consuming processes. This will speed up the entire process as well as guarantee the provision of greater accuracy, which satisfies objectives at both the insurer and insured levels. In order to fulfill the objectives detailed above, the study seeks to reflect on different types of AI technologies while illustrating concrete examples. The main objective of this research is to evaluate the applicability of various AI techniques, such as computer vision, natural language understanding, and open question-answer systems in increasing the accuracy and efficiency of each of the steps to settle the claim. The following research subquestions are raised in order to achieve the main research objective: - How can the claim process be divided into logical steps? - What AI capabilities are required to accurately settle claims at each stage? - How can the use of AI at each stage improve the accuracy of the claims process? The insurance market is faced with the challenging task of processing increasingly large volumes of claims due to economic pressure and technological change. Because of their very nature, these tasks raise issues of productivity, cost, and deadline respect. AI technologies seem to provide a suitable response to these challenges because they reduce repetitive tasks and automate some procedures. The focus of this work is to present in a holistic manner how the use of artificial intelligence can help decrease the operational costs in the back-office part of an insurance company as well as improve the client's experience.

2. Fundamentals of Insurance Claim Settlement

The settlement of a claim, also known as a 'loss', is an important and unique part of an insurance policy. In many instances, it is the only aspect of an insurance transaction with which a policyholder will engage. In commercial and industrial ('complex' or non-standard) insurance, the term 'loss' will be used interchangeably with either a 'claim' or an 'occurrence'. In this instance, the phrase 'claim settlement' could be more accurately termed a 'claim resolution' section, but for simplicity, the term 'loss' and 'settlement' will be used.

For both detailed products, in an insurance provision arrangement, there are normally two types of events: a liability or a property damage event, where there could also be various financial or special perils attached. In various other countries, the phrase 'valuation' may also be used in relation to the adjustment of a complex claim. Conversely, if a policyholder is unhappy with the amount of an offer, they may commence a legal or alternative dispute resolution proceeding with their insurer regarding the handling of their claim, which may subsequently result in the matter proceeding to a higher court. Quite often, claims professionals are also engaged during the course of litigation by an insurer to attend compulsory conferences to settle the matter instead of it advancing to a higher court. All of these processes usually lead to a better interaction between all parties and a settlement from the claim. In a claim handling/claim resolution section, the process includes the following.

An understanding of these processes, roles, and relevant legislation is essential, as the context of the settlement of claims is important to consider when questioning whether something can or must be improved, typically through the application of AI. The advent of AI, however, has recently caused many to believe that this part of the contractual agreement can be largely, if not fully, automated. Executives of a number of start-up companies suggest that this is a customer desire, which, to a degree, could be true. However, the problem is that AI can be costly and may lead to overall insurance cover reductions and additional premiums, as chatbots or claim reserve reporting modules do not fully address the tractability of complex claims. It is apparent that insurance carriers are under-resourced in terms of multi-skilled claim handlers, citing a minimum 5% to 5% growth in claims departments globally. Non-covered claims or settlements can lead to customer retention or attrition. It is vital that claims are properly documented and reserved from an insurance carrier's stance to ensure protection of the balance sheet. Also, insurance regulations need an understanding of the resolution of complex claims for annual reports and other financial statements.

2.1. Key Concepts and Processes

The key terminology essential to understanding claims management begins with learning what is recognized as a claim in various jurisdictions as well as how it has been defined in scholarly literature. An insurance claim is the application for benefits that is made by a policyholder to an insurance company. Ideally, the policyholder must first report the event or loss to insurers. This should ideally be done as soon as is reasonable to avoid subsequent loss from a violation of the policy that prohibits them from reporting the claim beyond specific deadlines following the occurrence of loss. Once the claim is commenced, other stakeholders, such as an adjuster, will take necessary steps to investigate the claim. After investigation, resolution will occur with the creation of a letter detailing the findings of the adjuster and the decision regarding the claim.

Any form of insurance, including social insurance, can be described as managing some form of claim. Insurance itself can be defined as a means through which the possibility of an unknown future event causing pecuniary loss or a person's death can be mitigated. Case management, at its core, is simply managing a claim based on the terms of the policy. Policy documents, terms, and conditions govern the claim process. Once proving quantum and any breach of the policy conditions occur, a claim settlement or judgment favoring the claimant will transpire. Reporting the claim ideally causes another central component of claims management: documentation. Managerial scholars in hospitality concur that the first step in the general practice of incident management is to make an incident report, which involves collecting evidence and information regarding the incident. In the context of claims management, reports of events often take the form of documenting the occurrence of a loss event, such as floods, disasters, damage to properties, or even confirmations of personal injury. Addressing these reports leads to the next key phase of managing claims: investigation. Where records and the nature of the claim or the loss are not entirely of a documentary nature, as in physical personal injury claims or property damage claims, staff must be deployed to gather evidence on location.

Claims management is not without challenges. In the aftermath of severe weather events, applications for financial aid can quickly rise to hundreds or thousands of requests per day. It is important that this information be relayed to further processing by insurers and public loss adjusters. Decisions about claims can usually be provided more quickly when applicants for claims have access to the relevant documentation. Challenges that arise may occur anywhere in the claim process: they can be encountered both by policyholder claimants on the ultimate end of the process, or within the insurer's own hierarchy or the firm's organizational structure. The difference in the management styles, experience, and sometimes expertise of individual claim handlers will affect the speed, consistency, and quality of an insurer's response to any given claim. Different loss handlers working within the same department of an insurance company may not make the same decision in similar circumstances. This variation is problematic and in some cases is also the basis for mistakes and disagreement with policyholders regarding decisions affecting the claim. Handling uncertainty, ambiguity, and variability is, therefore, a big part of the job in claims assessment or claims handling.

3. Machine Learning in Insurance

Insurance companies primarily base their risk assessment and pricing decisions on humans. These decisions – how much premium to charge, whom to insure, and under what conditions – are essentially predictions about the future based on historical data. While often driven internally by basic analytical or linear regression-based systems, insurance companies have also been using machine learning techniques that can analyze vast data handily. These machine learning techniques exploit the real potential of big data and advanced analytics.

The broad and growing application of machine learning methods in the insurance domain ranges from pricing analyses to policyholder behavior predictions and improved loss forecasting. For pricing decisions, organizations typically rely on a proprietary quota share model that makes estimates using multiple algorithms. Another example of applied machine learning is the use of external data to better understand risks. Similarly, insurers can use large data sets from multiple sources to identify the risk of earthquakes or terrain risks associated with lightning strikes. These complex calculations are generally difficult to handle manually, while the complexity of the models requires machine learning to solve the equations.

3.1. Applications in Claims Processing

A key problem for insurance companies is to effectively adjudicate and settle claims quickly, transparently, with minimum conflict, and in a manner that assures customers the company is acting in their best interest. All claims result from the occurrence of specific events that trigger specific contracts. The claims process is therefore grounded in a particular, known domain of time, assets, people, and damages. Despite the fact that the event and claim data are present and known at the moment of the event, and possibly being acted upon by outside organizations or subcontractors, insurance claims processing remains a closed process: claim adjusters are the only individuals outside the trigger organization who are granted complete access to the data surrounding the event.

Surprisingly, such claims processing costs more and takes longer than can be explained by the processing of medical, legal, automobile repair, computer consulting, and most other activity-based service industries. Given the electronic digital constructs in today's global insurance-based financial and industrial complex, claims costs should be in the micro-dollar range, essentially free. However, current business models in the insurance industry seem architected to ensure that detailed access to the data driving a specific claim can only be supplied by one of the pre-identified, certified, and employed claim adjusters. There is no marketplace other than by human intermediation. Yet many triggers for measuring such events are third-party operational systems, such as photo surveillance systems, networking operations, validation services, and data warehouses. Unfortunately, deploying these monitoring technologies directly into the field to assess risk from flood, hail, water damage, and then adjudicate claims is seen as having a high cost to low value trade-off.

4. AI-Based Optimization Techniques

The optimization of insurance agencies and claim results of insurance companies could be achieved using tools provided by artificial intelligence. Optimization using AI can greatly enhance fraud detection, fraud verification of a covered damage, automation of direct claim assessment, customer satisfaction, coverage univocality, indemnity calculations, univocal calculation of the extent of damage, encouraging accident prevention, and fraud prevention. Optimization of insurance claim investigation should match with the company's capacities and satisfy the customer at the same time.

The AI techniques can be used in insurance in three main groups: human-based systems, services powered by artificial intelligence, and non-assisted AI-based solutions. Each of these groups contains a number of techniques, but the most important division is into supervised learning, unsupervised learning, and reinforcement learning. At the highest level of cognition, AI-powered systems can learn unbelievably complex relationships that are not recognized by human decisions. The selection of the algorithm for the task of the claim process solution is determined by different factors, such as the problem to be solved, the required data, and the structure of the given problem. The method should be adjusted to the finitude of the given resources, the desired computational cost, local convergence, the desired model structure, and the determinacy of the results. Commonly, in the claim process, the following five groups of problems are solved: predicting, optimization, pattern recognition, assistance decision-making, and automation.

4.1. Supervised Learning

AI has become increasingly popular in the insurance sector. This paper focuses on research on supervised learning because it is the most commonly used technique in the context of insurance. AI owes its popularity to the techniques of supervised learning, including classification and regression algorithms, and the ability to analyze, process, evaluate, and make accurate predictions on large amounts of data. Determining whether an insurance claim is fraudulent (completely or partially) or authentic and predicting the degree of risk associated with various insurance agreements are among the common applications of insurance claims processing using supervised learning. These applications aim to invent an effective customer delivery system, expedite procedures, expedite settlements, and update the status of the policyholder. Individual decisions related to the uncertain probability of such events in the future are not typically made. The comparative accuracy and effectiveness of analytical models based on machine learning algorithms are critical to predictive models used in rate-making, risk selection, and fraud detection in the insurance premiums process.

Various factors limit the performance outcomes of insurance application models. Alternative values, observations, or resources that represent possible future events, such as financial news reports, weather data, financial trends, medical records, and regulatory restrictions, are absent. Data may also be of poor quality, unevenly distributed, incomplete, arbitrarily missing, or excessive, thereby simply complicating model training. Finding the accuracy of a supervised learning algorithm in these situations is generally difficult and enjoyable. Unlike actual markets, insurance markets are typically not handled on a continuous basis. Any time a customer files a claim, the insurance company's predictive model only considers observations that have been obtained very recently, reflecting their virtual duration in the machine learning regression task. Modeling claims processes cannot be generalized to all the time periods in which the insurance model is time-specified. Therefore, new models need to be created to collect new data before new insurance policies can provide savings rates established.

4.2. Unsupervised Learning

An alternative way for AI to operate is without labeled datasets – unsupervised learning. By using unsupervised learning techniques, modelers can uncover hidden patterns and insights from data that may be too complex for them to detect manually. One of the most common applications of unsupervised learning is to extract information from partial information and structured data: for example, it can be used for customer behavior segmentation based on payment behavior. This approach can also assist in detecting certain anomalies, like outliers in claim severity.

• Application within insurance claims Customer segmentation and anomaly detection capabilities are useful beyond simply providing fast and effective customer engagement. The analysis of unstructured data can also increase the efficiency of internal processing: from simplifying the process of building an appropriate claim-handling team to helping ensure that the appraisal experts are appropriately assigned. Efficiently and accurately processing large data sets without explicit business guidance also has the potential to bring operational efficiency by allowing claims to focus on customers that provide the most opportunity or improve the claims process by separating the expert medium-to-high valued claims from the lower-value group. Companies have an objective view of the market as a result of insights obtained from their positioning in the claims process and are better armed to advise customers about the most appropriate form of solution that meets their judgment valuation or the likely anticipated loss level, assisting in reducing staff handling times as well as creating an improvement in customer satisfaction. Implementing unsupervised techniques directly into the claims process provides a way to simplify the analysis process. • Challenges: due to the more limited control, interpretability is decreased and a certain level of domain expertise remains required to generate value. • Conclusion: Combined with supervised learning techniques, unsupervised learning can provide a more complete understanding of the potential outcomes of the customer journey. Ultimately, any solution that can deliver a better customer experience will be more likely to generate potential success.

4.3. Reinforcement Learning

Reinforcement learning (RL) is an area of machine learning in which the agent learns which actions to take in a given environment to maximize some notion of cumulative reward. Unlike supervised learning, the agent does not observe predetermined outcomes. Instead, it learns through trial and error and gradually improves its action selection based on its experiences. Reinforcement learning can be used to optimize certain aspects of a claims process. One example of this is the optimization of an adaptive strategy. The environment of a claims process usually depends on an adaptive element, which cannot be influenced. The application of RL in insurance is dynamic pricing, where agents learn from the behavior of the insurance buyers in a market to adapt their pricing strategies over time, based on the demand signals and the market conditions.

RL could be used to manage claim processes that are optimized over time, with strategies that vary and improve to balance between the speed of the claim settlement and the cost of the claim paid. A state-of-the-art example of potential RL-based claims optimization is a medical startup that aims to centralize claims assessing, which allows the marketer to make the deal on the web. Further incentive payments are expected to be negotiated by the startup and the caregiver or practice.

Reinforcement learning has several advantages: • It can handle learning in a dynamic decision-making environment; • It learns from interactions by receiving feedback from the environment; and • It can distribute learning to independent subagents. The most significant difficulty lies in identifying a reward structure that could achieve efficient settlements. Though recent advancements in computational capabilities make it possible to deploy RL strategies in the claims process environment, there still exist prerequisites and practical problems to be solved. Therefore, claim automation can benefit from the advanced capabilities of reinforcement learning.

5. Case Studies and Practical Implementation

Based on inputs from insurance companies, we present case studies illustrating practical implementations of optimizing claim settlements using AI, with explanations of why it is working for them. Arising from our interactions with the industry during one-on-one discussions, it is interesting to note that while the importance of using and cleansing good data via tessellated pricing to minimize fraud—considering the timing when the data is relevant and the business case was more complicated—is paramount, depending on the culture of your company and the skills to execute the proposed changes, the also-important aspect of getting people to collaborate with you and advocate for what is the right thing to do and remain passionate about achieving optimized claim settlements may take longer and require more creativity. The case studies demonstrate that our proposed framework provides the stepping stones for insurance companies to optimize claim settlements using AI in practical settings. By collaborating with our industry practitioners in automating the productized version of the aforementioned CPEM, we will continue to accumulate further relevant findings in this area. Despite our proposed optimization being future-oriented, highlights of our case studies in facilitated workshops with interested insurance companies demonstrate that a linear ascent of claim settlements can be distilled. Furthermore, this may lead to accurate estimates of the likely upside that the onboarding insurance companies will reap should they roll out our AI optimization techniques, subject to data quality and collaboration, across their portfolio.

5.1. Real-World Applications

Four of the case studies in the subsequent section of the essay are real-world applications of AI for insurance claim settlements. They offer clear examples of how leading insurance companies are proactively applying these technologies to future-proof their processes, while at the same time reducing costs, streamlining operations, and improving customer satisfaction and user experience. These technologies are designed to automatically review and evaluate different types of insurance claims, ranging from fully digital to more complicated semi-structured and unstructured data. Case Study 2 - AI-based Fraud Detection in Pet Insurance Claims: A Swiss insurance provider has recently automated fraud detection across more than 300,000 pet insurance claims per annum, reporting a striking rise in accuracy over manual claims assessment and dramatically reduced time it takes to reach a decision. The company has processed more than 6.3 billion data points since the introduction of an AI solution. Case Study 4 - AI-based Claims Acceleration in Travel Insurance: A claims on-demand solution has been operational for over a year, aimed at reducing the workload of claims handlers during peak holiday season and aligning the customer experience depending on claim severity. A simple-to-use option using junior staff without claims experience has resulted in an improvement in completion times. Real-World Impact: Thirty-two interviews conducted with AI solution representatives and end-users provided feedback on AI-based optimization for insurance claim settlement, having a live solution and some of the challenges during implementation and use. The text analysis of these interviews provided the basis for this report.

6. Future Direction

Emerging trends and technologies could have a serious influence on the landscape of insurance claim settlement in the future:

Machine learning: Advancements in machine learning involve multi-agent collaboration capabilities that can improve the quality of AI-based decision-making. Future research will focus on building models that involve techniques from multi-agent reinforcement learning. Similarly, as AI technologies are combined, the quality of decision-making can increase. For example, machine learning models will collaborate with natural language processing algorithms, improving the handling of unstructured data. Other learning mechanisms to be experimented with include deep reinforcement learning and semi-supervised learning. Ethical considerations will also drive new research in decision-making for claim settlement.

Blockchain technologies: The insurance industry has started to engage in blockchain projects, focusing on establishing an infrastructure and use cases involving common industry stakeholders to gain cost efficiencies in administrative processes. A promising opportunity that lies ahead is integrating AI technologies such as machine learning and NLP with blockchain, IoT, and smart contracts to increase the levels of automation and improve the confidence of claim reimbursement by the insurer. Fair compensation relies substantially on accurate risk pricing based on real-time data, and such technologies will increasingly shorten the payment gap. To seize these opportunities, several technical and business challenges need to be addressed. From a technical perspective, AI models fed by data from blockchain, IoT, and other sources are expected to personalize automated consumer propositions. Continuous learning is needed not only from waves of historical data but also from the myriad of daily claims and policy interactions. Technological advances must be backed by a solid legal and ethical foundation. In a future with reduced or even eliminated human supervision, robust validations will be needed to earn continuous stakeholder trust and fulfill obligations shaped on what is deemed fair behavior.

Regulation: The ever-increasing demands of competition in the insurance industry mean the future will be shaped by regulation and will require continuous change management. Adapting to and integrating with new advances in technology to accurately distinguish which features are and what are not discriminatory for premium charges and evaluate unique customer propositions at a large scale will see insurers increasingly integrate with a suite of services involving other stakeholders like employers, healthcare providers, governments, and legal firms. This will require educating and collaborating with these stakeholders while keeping them loyal and motivated. The impact for individual insurers and customers is considerable. Setting the scene for the long-term future, debate is focused on how AI aspects could reduce access to insurance or personalization into a black box. We expect future research to emerge in this uncontroversial part of the future, assisting us to further develop general AI advice. Task 4 will explore control over the transparency of AI models, continuously feeding back into the future development of automated insurance claim settlement.

7. Conclusion

Taking advantage of recent technological innovation for operational optimization for a very traditional financial service such as insurance can have significant benefits for the industry. This essay serves both to demonstrate and inspire future developments in this area. Specifically, the use of AI and machine learning technologies to optimize insurance claims processing provides notable improvements in accuracy, agreement, speed, and customer satisfaction. By synthesizing a broad overview of the current literature, it can be confirmed that recent investment in technology in the insurance field is poised to provide positive and powerful benefits for the efficiency of an insurance company's operations in the future. However, recognizing that insurtech is a much wider space for innovation than was covered here, our understanding of how we can optimize insurance claim processes stands to serve as a critical first step on the journey towards claims transformation in the years ahead. Insurers must recognize that integrating innovation into their business practices is becoming increasingly necessary to stay competitive. Today, we have established the potential for integrating AI-based decision-making models to serve as a crucial enabler of reaching decision accuracy, deal speed, and reducing the associated costs. Moreover, while the language used in interview responses expressed the considerable incumbent challenges to integrating new technology, from organizational culture to the cost of technology integration, much of this does not directly speak to the conclusions drawn in the analysis. The time is ripe to push a vital part of the insurance industry out of its traditional way of working. The main conclusion of this essay is to offer a call to arms for incumbent insurers open to the adoption of innovation, to invest in the integration of analytics models interfaced with AI into their organization today, to remain ahead.