Cloud-Based AI Systems for Real-Time Underwriting in Recreational and Property Insurance

Lahari Pandiri

SR Systems Test Enginner
Email: *lahripandiri[at]gmail.com*
ORCID ID: 0009-0001-6339-4997

Abstract: ***Using the Cloud, we develop an AI algorithm for multi-dimensional risk analysis with real-time demo risk evaluation. Our innovative approach to identifying risk surely improves the comfort of conclusion about demanding some terms and conditions for insurance, proposing for cancellations and declines, especially when positive and negative risks are presented together. By applying risk-based evaluation to museum income insurance, we demonstrate how fine is the decision obtained using original loss distribution approach to find safety loading, available thresholds for loss probabilities, reinsurance structure with the use of quota share and excess of loss contracts. Two aspects are unique in the project: being guided by decision trees, the rules behind demisking decisions are formulated as early warning artificial ideas, and, more importantly, it is the first paper where visual parts of HRM are treated as HRM influenced approval or negation of proposals for real-life, well-motivated decisions. These advantages make our algorithm attractive for the business processes of proposals for prediction and negation of decisions through demission ranking modeled by their cash flows. They allow us to extend the use of an innovative approach to HRM presentation with visual local system images on other patterns of LDA. The suggested risk-based methods make it possible to take reputational risk into consideration, classify the portions of profits and losses into the private, public, and proprietary ones, and set safety loading for any group of cash flows.***

Keywords: Cloud-based AI, real-time underwriting, recreational insurance, property insurance, risk assessment, predictive analytics, underwriting automation, scalable systems, machine learning, cloud computing, insurtech, AI systems, real-time decision-making, digital underwriting, insurance technology

1. Introduction

In competitive insurance markets, profitability depends on accurately estimating the future loss amounts for any given insurable risk, which is complicated by significant uncertainties. It is important to estimate such risks at the time of writing the insurance policy, through the underwriting process, so that the risks are appropriately assigned to insurance pricing structures. In most property and casualty insurance markets, personal insurance such as recreational and property insurance is typically considered "low hanging fruit," where loss costs are much less than comprehensive policies and high volume activity leads to profitability. Underinsured or improperly insured clients in these segments provide and require additional service, and insurance underwriting must reach out to engage them and bring them onto the correct pricing structure. Consumers now use advanced digital tools to obtain, compare and purchase insurance products, including recreational insurance, from many potential providers. Emerging technologies including the Internet of Things and other innovative data sources being used by other service-centered industries are not yet widely utilized in insurance underwriting and pricing. How can we improve the underwriting of personal lines insurance products through the thoughtful application of these technologies? Insurance pricing and risk models are often based on minority specialized actuarial professional skills and analytical tools. Cloud and AI systems now provide easy user access to much more powerful and timely data analytic and data architecture tools. The time is right for an insurance startup to break into the personal insurance line market utilizing these technology tools from a shorter-time-to-market, lower-cost and agile strategy in order to effectively compete against existing insurance organizations with highly developed traditional methods and routine costs for writing policies.

2. Overview of Cloud Computing

Computer science defines cloud computing as a model for enabling on-demand network access to a shared pool of configurable computing resources that can be rapidly provisioned and released with minimal management effort or service provider interaction. This definition implies five key characteristics, namely: (1) On-demand self-service; (2) Broad network access; (3) Resource pooling; (4) Rapid elasticity; and (5) Measured service.

The essential characteristics of cloud computing are as follows. First, on-demand self-service means a consumer can unilaterally provision computing capabilities without requiring human interaction with a service provider. This minimizes overhead because service provision can happen at any time of day or night. Second, broad network access means that cloud capabilities are available over the network and accessed through standard mechanisms that promote use across a wide range of client platforms. Third, resource pooling means that the provider’s computing resources are pooled to serve multiple consumers, with different physical and virtual resources dynamically assigned and reassigned according to consumer demand. This provides a large amount of capability and allows the provider to serve many more consumers than traditional IT approaches. Fourth, rapid elasticity means that capabilities can be provisioned and released in elastic fashion, in some cases automatically, to quickly scale out and in commensurate with demand. Finally, measured service means that cloud systems automatically control and optimize resource use by leveraging a metering capability at some level of abstraction appropriate to the type of service. This allows for transparency for both the provider and consumer of the utilized service.

3. Artificial Intelligence in Insurance

The insurance industry, still going through a digital transformation, is leveraging Artificial Intelligence (AI) to sustain its operability in digital economy whilst trying to improve its efficiency and productivity. Artificial Intelligence refers to a simulation of human intelligence in machines that are programmed to think like humans and mimic their actions. There are various subsets of AI, which can be associated to technological systems that perform tasks a human would ordinarily perform for the plain reason of augmenting and amplifying human abilities. Thus, in a supporting sense, we can say that any application that augments a human's ability represents a sort of assisted intelligence. As such, AI generally comprises Expert Systems, Machine Learning (ML), Natural Language Processing (NLP) and Robotics. Artificial Intelligence applications leverage some of these technological subsets and offer solutions to reduce costs, decrease cycle time, improve compliance, enhance efficiency and better customer experience.

When it comes to the insurance industry, especially underwriting, they are facing several challenges. Insurers are still relying on outdated systems that, in these days of constant change, are ill-suited to address the high underwriting volume and demand for quick turnaround time. New insurance entrants, which often rely heavily on AI and InsurTech systems, are currently offering lower premiums and better overall customer experience. In order to remain competitive, insurance companies also need to implement advanced technology. Applications based on ML and NLP could provide different advantages for insurers, and especially underwriters, and could improve efficiency across key functions, help with risk assessment and analysis in real time, relieve underwriters from extra work and repetitive process and manual evaluation of risk and risk selection, and provide better and more personalized service to clients.

Figure 1: AI in Insurance Industry: Benefits & Use Cases

3.1 Machine Learning Algorithms

Machine learning is driving the most important novel technologies in predictive analytics, including various techniques for supervised and unsupervised learning. Supervised learning is a learning system whose function can be characterized by the input-output data sampled from an underlying true but unknown probability model. The supervised learning system must take data-labeled training data, estimate the function, and then apply the function to a new unlabeled input datum to produce a corresponding output. The loss function imposed on misclassification quantifies how much the estimated function is penalized when the output produced for a given unlabeled input datum does not coincide with the true output. The goal of supervised machine learning is to minimize this cost function by efficiently estimating the mapping from unlabeled input to labeled output. In the insurance underwriting space, the most widely used supervised learning algorithms include classification trees, deep learning neural networks, gradient boosting, kernel-based methods, nearest-neighbors, random forests, and support vector machines.

Other learning tasks are considered variations on supervised learning, such as multi-instance learning, sequence labeling, ranking, and transductive learning. Practical implementations of these various supervised learning methods are found in freely available libraries. Multiple prediction functions can be combined to augment prediction accuracy, which usually improves output prediction performance over any single estimated predictive function. Stacking of multiple computed classifiers includes error-correcting output codes, bagging, boosting, and rotation forests. Transductive learning uses a small amount of labeled data and a large pool of unlabeled data to produce high-confidence predictions for the unlabeled data.

Equation 1: Real-Time Decision Latency

$$RTDL = T_{Input} + T_{Processing} + T_{Response}$$

Where:

- $RTDL$ = Total latency from data input to underwriting decision
- T_{Input} = Time to receive and validate input data
- $T_{Processing}$ = AI model processing time
- $T_{Response}$ = Time to return result to user or system

3.2 Natural Language Processing

Natural Language Processing (NLP) allows computers to analyze spoken and written language and is an essential area of AI implementation. It is necessary to translate human input, as evidenced by its growth from 460 research papers during 2002 and up to January 2019, to 118,000 corresponding research papers over the previous year. We can find most implementations in chatbots, virtual assistants, and machine translation. For our work, we focus on NLP for chatbots as virtual assistants in insurance. Chatbots offer realistic interactivity to users, both in their answers, with an extensive line of pre-programmed answers, and in sense generation, becoming less scripted by learning from their interactions through Reinforcement Learning. Chatbots also create a sense of identity thanks to carefully built personalities that make coming back a pleasant experience. Therefore, chatbots enhance the prediction, personalization, and sense-making capabilities of insurance providers.

The general process for training NLP models for chatbots is as follows. First, a dataset must be created. Public datasets only cover specific domains, resulting in low identification rates for users outside those datasets. Otherwise, the insurance companies could share their datasets with providers. Then, the dataset is pre-processed to ensure textual clarity, focusing on understanding response generation time and required response diversity. Finally, models are implemented that process the dataset conversationally, such as Retrieval-based models, that select the proper response from the dataset and Generative-based driven models that generate new unique responses. Due to the low identification and diversity constraints, most chatbots implemented in industry do not integrate Generative-based models and are driven by Retrieval-based models.

4. Real-Time Underwriting: Definition and Importance

When a new insurance application is received, it can go through a lengthy and repetitive underwriting process that results in a delay in time-to-quote. The applicant may have to wait many days to find out whether the request for coverage has been approved, and the applicant can always choose another insurance company to get a quote during the underwriting process. Because applying for insurance is not a frequent event, applicants tend to switch insurers to find the best price whenever insurance quotes from several insurers are available. In this age of technology, where everything is done online and in real-time, many clients lose interest in the potential service and choose other insurers to get coverage for property and recreational insurance.

Real-time underwriting is a solution that provides decision-makers and key stakeholders with instant and relevant information, allowing them to make informed decisions. Even though the insurance industry has been working hard on expediting the underwriting process to offer expedited services and real-time quotes to customers, the effort has been more challenging and complicated than expected. This has motivated key stakeholders to try machine learning and artificial intelligence to help extract both structure and unstructured information in order to resolve some of the most tedious tasks in the underwriting process. Automating insurance services allows insurers to better manage risks while minimizing costs - which, in turn, allows for efficiency in the quoting process.

5. Recreational Insurance: Unique Challenges

The development of cloud-based real-time underwriting systems is a critical business necessity for both property and recreational insurance. However, the characteristics of recreational insurance add an element of urgency because of the long-term effects of climate change on natural-hazard risk that render underwriting decisions within the current long-term cycle of growth in claims and losses perilously blind to the future. The long-term impact of extreme events on premiums and losses – whether due to market-based or regulatory compulsion – is always greater than the concurrent effects, causing both to increase during periods of peak weather sensitivity. The long-term business case for the development of data-driven models for long-term risk forecasting is, therefore, most compelling when loss ratios rise substantially during these peak periods of sensitivity.
Recreational insurance has several distinct but interrelated features not present in property insurance. The seasonal nature of the policies makes both reinsurance and pricing collection more difficult. Their high volatility amplifies the need for a sophisticated, nuanced modeling approach to loss events in order to optimize product design. Personal insurance loss portfolios overall are converging towards relatively quick recovery because structured data assessments are providing near-instantaneous access to loss locations. The more significant problem is secondary and cumulative losses from undetected elements in interior structures. Loss-settlement times can vary considerably across different region-/peril/cause-loss clusters, which make geographic and temporal data-cut stratifications more complex. Furthermore, events such as tsunamis can take multiple seasons to settle due to policyouts occurring in subsequent seasons.

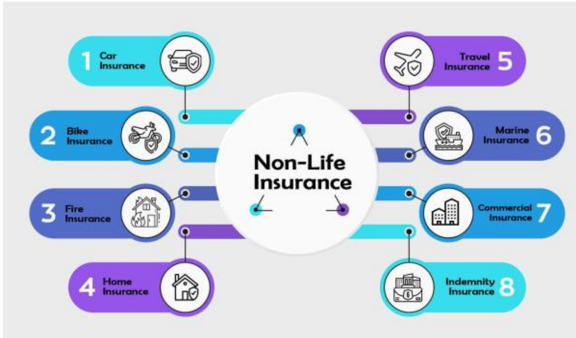

Figure 2: Non-Life Insurance Policy

5.1 Risk Assessment

It's no small task to assess the risk exposures for short-term rental properties, since there can be so many additional risk factors, such as the site of the property and what's nearby and the characteristics of the guests. Therefore, the core short-term rental guest risk scoring feature set differs from that of traditional insurance by: Number of guests. Short-term rentals are generally booked by families, and at times large family reunions, which push the guest count significantly over the traditional maximums allowed. Even homes built in pre-1970s single-family zoning districts are often converted into large multi-family short-term rentals, housing parties with dozens of guests. Ceiling or access violations. As with condition violations, in addition to wear and tear and building code violations eroding a property’s fire safety and building integrity over time, misbehaving guests with or without pets can cause horrific damage to short-term rental properties while partying and creating raucous events. Zone risk factors. Typically, recreational and commercial zones do not allow for multi-family short-term rentals, and even in single-family zones, there are limits on the number of potential guests. A concentration of all types, whether listed or unregistered, could attract college parties or tourist mischiefs, resulting in higher risk for those properties close to trouble. Rental history. Even if the property is relatively new or is not in a tourist district, a property with negative guest reservations could hinder risk. However, if the property is established and has a good record for guests over time, then the risk may be less. Inspection and exclusion based risk features. Rather than just listing whether a property has smoke detectors, alarms, or sprinklers, much more interesting are rules governing their placement, activation of fire alarms, filters for HVAC, and more exotic systems such as sprinklers and active structural monitoring systems that watch for and prevent property damage. Moreover, the type and year built are relevant.

5.2 Customer Behavior Analysis

Customer behavior is of primary importance during the product design. It is not sufficient just to provide products that policyholders would need and rely upon; these should be sufficiently understandable and accessible for the end-user. The insurance market is trendy, which demands searching for the product mix and adjusting it to the rapidly changing needs of different segments of the society. Insurance should cover the actual needs. Moreover, the product coverage and design should address behavioral biases inherent in recreational insurance. Customer behavior is of primary importance during the product design. It is not sufficient just to provide products that policyholders would need and rely upon; these should be sufficiently understandable and accessible for the end user. The insurance market is trendy, which demands searching for the product mix and adjusting it to the rapidly changing needs of different segments of the society.

Insurance should cover the actual needs. Moreover, the product coverage and design should address behavioral biases inherent in recreational insurance. Policymakers often ignore the statements appearing from insightful behavioral economics incurring error and bias and damaging both the industry and insureds. Products should be designed in such a way that insureds can understand what they are purchasing and will supposedly need. Furthermore, there is a problem dummy product – it is placed on the market with ignoring the actual needs of customers. Dummy insurance are designed only because they are subjected to the unique nature of tourists or no one else does. Dummy products violate the two basic principles of insurance: differentiation and protection against risks. They are practically content less.

6. Property Insurance: Market Dynamics

The majority of premiums are charged by property insurers and the largest cost in this kind of insurance is claims payments. Yet, analysts know little about property insurance market dynamics: how claims are initiated, how claims are settled and the severity and duration of claim events. The uniqueness of the property insurance claims process is that insured stakeholders may delay initiation but after initiation resolve the claim in conjunction with the insurer quickly and these two stakeholders jointly have low control over the severity and duration of the events that trigger the claims. Claims data are usually proprietary and highly contextualized about particular insurers, lines of business and geographic areas. The few empirical studies rely on broad panels of property insurers or a single large insurer. Commentary is at best circumstantial and there is no linking theory. The insurance claims process can be fuzzily described as a transaction cost negotiation process.

In property insurance, compared to life, workers compensation and health insurance and primarily commercial liability insurance, premise hazards and the pricing of physical liabilities are much simpler and easier to price at initiation. Insurers levy a premium at initiation based on risk pricing under severe competitive conditions that vary on the low frequency of claims compared to the popularity of policies issued and the premium collected. Strong surplus and reserve adequacy regulations prevent the strategic manipulation of claims payments at exit to distort prices or increase profits. Claims are primarily provided by state regulators who impose penalties on insurers who do not meet minimum claim payment adequacy standards for insured consumers within preset time intervals.

6.1 Claims Processing

Entering the Insurance industry is normally defended as possessing a competitive advantage over incumbents, or as being a natural evolution of adjacent industries processes, e.g. fintech in the area of loans. In the case of Claims Processing though, it is more than likely for any new entrants responsible for the kiting or support technology to be pushed actively, or incidentally, to develop a solution-agnostic kit approach. The number of specialized players should cross with a certain concentration on a few frontrunner incumbents to signal the establishment of a somewhat sufficiently concentrated and rugged architecture. The degree of remaining fragmentation could explain either non-optimal results or the fact that for the time being, no better-performing solution-agnostic kit is available and clients are motivated to go proprietary.

Equation 2: Underwriting Risk Score

$$URS = \sum_{i=1}^{m} (F_i \cdot W_i)$$

Where:

- URS = Total risk score for underwriting decision
- F_i = Individual risk factor (e.g., property age, location)
- W_i = Weight assigned to risk factor i
- m = Total number of risk factors

Back-end AI-based solutions or kits that help with the vertical streamlining of claims processing should be of lower concern of insurance executives due to their back-end playing a less disruptive role that would simply serve to optimize back-end operations. The only potential for disruption could come from the fact that proprietary systems would be designed to bring cost efficiency to the level of pure placement costs in stock market parlance. Automated assistants specialized in answering FAQs, AI-based organization of incoming messages, proposing templates, tagging purposes, allowing to build checklists, literate digital agents who could at least to a degree learn the company's vocabulary and process templates in order to know what messages or actions would be appropriate from what situation, as such fall outside of the insurance industry. However, what needs to be carefully monitored are the fast-development behemoths that build systems covered along the lines noted.

6.2 Policy Pricing Strategies

The effective provision of care cannot be separated from the affordability of insurance policies; however, neither can the affordabilization of insurance policies from the effective provision of care. The first aspect of inquiring into the negative correlation between the conditional expected loadings in the demand for insurance and its price, as ensembled in the law of demand, is developed within the self-interested modus operandi theory of the act of insuring. The pricing strategy of an insurance company must comply with its own self-interest and/or shareholders' self-interest. To comply with interest, policy pricing must be subject to profitability constraints, and studies of the influence of price on the demand for insurance require elasticity on changes in policy normal and demand; the equilibrium is achieved at a price at which is neither a negative nor a positive differential of the demand for insurance with regard to its price, however, not avoiding engaging in the act of insuring: The price which maximizes a company's profits is at a level greater than that at which demand is at its highest.

For both life and non-life insurance, there is a consensus that policy prices are primarily a function of the demand for insurance. Life insurance is normally a luxury good, that is, as the income of the consumer rises, the proportion of income spent on it rises. Indirect estimates of the price elasticity of demand suggest that life insurance is not very sensitive to price changes, while the non-life insurance is more responsive. In practice, however, companies are typically at a loss in estimating demand functions for the long run and the short run. The first formulations of the demand for insurance examined how the decision to purchase is made, but there appear to be a considerable number of determinants that affect the demand within the month or quarter. However, most of the empirical studies of the demand for life or non-life insurance focus on examining how the short-run demand functions behave.

7. Integration of Cloud-Based AI Systems

The cloud-based AI solution creates quick evaluation AI subsystems on the cloud that answer underwriter requests in real time, retrieve the needed documents, input the demand data, and compare its risk evaluation with the decisions of the like properties in the region. If the evaluation is confirmed, it is input to the main AI underwriting system for training. The main system serves multi-domain and multi-task needs by answering various underwriting tasks for different insureds or objects at the same time, such as pool flood prediction, building fire risk, bike theft, commercial theft, and home fire risk in a given time.

Equation 3: Cloud Scalability Index

$$CSI = \frac{R_{Peak}}{C_{Base}}$$

Where:

- CSI = Scalability index
- R_{Peak} = Peak number of underwriting requests processed concurrently
- C_{Base} = Baseline system capacity without cloud optimization

The main data sources include past claims data with attributes that characterize their root causes, e.g., disease, weather, conspiracy, time, and location; characteristics of the insured person and object; and the features of the insurance policy, such as price and coverage amount. Even for early-stage small datasets, ML classifiers analyze and extract the demand risk flags that dramatically require attention. The flagged achieving much higher demand risk rating than the without-flagging offer a good merit in ML classifier training. Thus, small datasets can instruct high accuracy AIs in the early stage to reduce losses and attract statements of organizations or agents with controlled demand-risk properties.

In the AI-enabled risk pricing and classification area, many models and applications classify risks and assign a variable price to the expected loss. However, these models do not specify the actual pricing implementation and the property features. We show in this chapter our cloud-based AI implementation of these models for underwriting and pricing and describe its architecture. The architecture includes a cloud-based AI subsystem for fast evaluation using cheap ML, a cloud-based system manager, and a fast cloud-based data production manager based on ontologies.

7.1 Data Management

Consider the following quote: “Data is a fundamental component of cloud risk management, and it needs to drive the overall risk message. Cloud service providers need to take a hard look at how they manage data to be trusted by their customers to provide the risk management mechanisms that properly protect their data.” The importance of data management cannot be overstated. Data describes the characteristics of the environment where the business transacts, i.e., company activities, policyholders, and related risk or exposure information. The quality, completeness, timeliness, and cost of accessing and storing data directly influence the AI models’ accuracy and predictive performance. Directly related to data is whether an organization has a data-driven culture that reinforces making strategic decisions based on the use of data analytics in operations to increase efficiency, and in developing and monitoring AI models to optimize outcomes.

Companies in the insurance and finance industries are in the unique position to leverage a treasure trove of historical data. While internal data can be used, additional external data sources can greatly enhance predictions of business outcomes. For example, publicly available data can provide pertinent data on weather and economic conditions. Private data sources can be collected by companies. These sources contain predictive information on a variety of factors impacting risk. Today, prediction models developed to identify weather risk and assess its impact are often too simplistic in isolating the relevant variables. The models need to be more tailored, nuanced, and customized, and predictions need to be updated more frequently. The greater reliance on

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big data analytics in reducing costs and enhancing speed relies on AI. The need for speed has created what is termed real-time marketing where predictions are made on the customers' needs at the time of need based on the data collected at that moment.

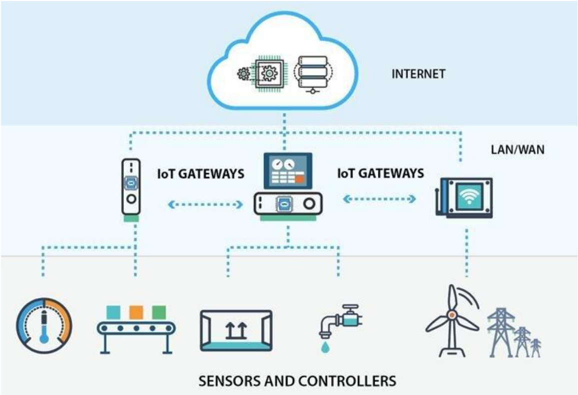

Figure 3: Illustration of cloud computing and IoT integration with AI-driven manufacturing systems

7.2 System Architecture

This section presents a cloud-based AI system architecture for underwriting in LI markets by providing tools for both humans and AI agents. Underwriting is hypothesized to be a hybrid-intelligence system, where human underwriters work together with decision support systems that utilize modern AI methods and cloud technologies. The system is capable of collecting the necessary data for the underwriting decision-making process and its design is based on the necessity of various parameter locations, and the manner in which the design is impacted by the degree of segmentation of the cohort and the amount of data needed to infer the parameters, and the nature of the relationship between the created parameters and the expected loss for that segment of the cohort. Finally, this architecture allows for the integration of other functionalities that enhance the efficacy and efficiency of the underwriting process. These functionalities range from alternative models for specific cohorts, to evaluating behavioral nudges for enhancing the likelihood of achieving desired behavior by the insured, to tools for the human expert underwriters responsible for conducting validations of specific cases, to a camera crew that collects submissions of documents evidencing certain parameters for the guide for documents required by the expert human underwriter.

The AI-based system architecture presented here addresses various levels of autonomy for the AI agent, and includes human expert systems that allow for inspections of special cohorts by human experts with provided tools for rapid decision-making regarding cohort actions. However, a special innovation is the definition of an additional layer that collects data and provides feedback to the AI decision support system for incorporating the additional information into its operations, thereby closing the loop. The cloud technologies allow for flexible deployment at the local and at the company levels.

8. Benefits of Cloud-Based AI for Underwriting

While some advantages of using cloud-based systems for underwriting are valid for any cloud-based system, combining the cloud-based paradigm with AI systems offers interesting features for the organization. Among the stated advantages of cloud-based AI systems are low cost, enormous scalability, process improvement, speed, and increased accuracy. We address each of these relevant issues with applications to the insurance underwriting process.

The use of cloud-based systems for AI reduces costs. By adopting a pay-per-use mode and keeping resources in the cloud that were previously installed internally, the organization avoids spending in IT infrastructure, which implies a cost of dead capital; it transfers part of the risk of high spending, related to the change in the volume of business, to the cloud provider; and it can easily scale up the number of workers needed for AI-related tasks, all of which leads to a reduction in overall costs. In practical terms, using the cloud reduces the costs of keeping AI models up to date. The same advantages of outsourcing the systems do-it-yourself to a specialist system usually have, regarding scalability, sharing of development costs, and access to quality workers, are enhanced when undertaken in a cloud-based mode. Accident-prone business lines can be assigned to external actuarial firms. Those firms have the information on high-risk clients in multiple companies to create the model required to analyze those risks.

Cloud-based systems reduce the time to deploy ML models and increase the accuracy of the description of complex processes. A serious problem for ML projects is the high processing time involved in batching the data, in the case of project creation, or checking the data integrity, in the case of model updating. Processing, which is usually very high when it comes to ETL processes, is always done in internal systems. When the needed resources are shared and used in a cloud-based mode, the time involved is reduced due to the use of more powerful resources. Furthermore, cloud-based AI architectures allow the completion of an iterative fast-prototyping process, which is the trademark of ML engineering, to be parallelized.

8.1 Cost Efficiency

One of the major benefits that the Cloud can bring to AI Systems, including those created for real-time underwriting decision support, is Cost Efficiency. In general, cost of new technologies is usually calculated for a business within the concept of TCO. As soon as the company uses this Cloud-based solution at scale, the Cost of Ownership can be very advantageous, as both Cloud Suppliers and Developers choose to heavily decrease the cost of Training and Deployment of AI Systems. Their efforts are oriented to acceleration of training cycles and deployment.

As a result, the costs of Cloud-based real-time decisions systems drops down to dozens or hundreds of dollars. And even when real-time decisions are not so numerous, still the Deployment of Cloud-based AI System can cost only a few thousands or dozens of thousands of dollars, bringing great business value. It is really important for businesses of any size – small and large, insurance agencies that can afford the Cloud-based System at first and insurers that will choose to

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have the service for many customers, internalizing the expenses by Revenues and TCO, but not for Annual Losses.

Also, when both the questions of Business Value and Costs of Technology are solved, there is some additional minor Cost Advantage. The insurers will not need to invest heavily in Hardware or Software to create their own Infrastructure, nor they will need to invest a lot of resources into support of its efficiency and security. The Data inside the AI Model will be stored safely and with no resources invested to make this Security happen. The Data Storage and Transfer Cost would be minimized thanks to a proper setup of Cloud Services used by the Business.

8.2 Speed and Accuracy

There are three considerations which influence the decision of whether to underwrite a policy. The first is the speed of the decision-making process, the second is the accuracy of the result, and the third is the cost of the decision making. Speed and accuracy are core attributes of many decision-making processes. Although these attributes are often traded off against each other, there is considerable interest in the potential for digitization to improve the speed and accuracy of decision-makers. Our research indicates that the hybrid automated expert model can significantly increase the speed of decision making, and the use of a more accurate decision-making engine can help improve the articulation of boundary conditions for the underwriting decision, and help reduce the level of auto-declines or other rejected submissions.

An interesting aspect of speed and accuracy is the impact of speed on the process of financial underwriting. The quotes for auto insurance can be decided in a matter of seconds or minutes. Certainly, the computational speed of an interesting AI process is sufficient for that. Financial underwriting can stretch on for weeks if not months. The question arises as to why such a comparatively simple underwriting process for auto insurance is so fast, and yet financial underwriting can last so long. The approaches used are generally known. An insurance company has an extensive database of drivers which is collected over many years, and therefore there is a great deal of data to train the underwriting model. There is a relatively limited number of boundary conditions that can lead to a comprehensive decision whether to underwrite an auto insurance policy.

9. Challenges in Implementation

Real-time underwriting in personal property and recreational risk insurance nurture expense challenges to actuaries and insurance companies as operations costs for analyzing a risk may be greater than the underwriting profit. Cloud-based AI underwriting systems expand storage capabilities and processing power and enable worldwide access to underwriting agents. Highly selective machine-learning-based apps are able to deliver underwriting solutions in seconds in a worldwide market 24 hours a day and 7 days a week, enabling specialization strategies for those insurance companies willing to face the challenge. However, perceived and real risks threaten the development of an innovative and profitable AI-enabled insurance model. Responsibilities, cybersecurity, data management, accounting, and other risk and insurance regulatory compliance issues must be resolved to create a favorable environment for the digital real-time underwriting operation.

Data sharing is an ever-controversial matter, and after the breach of trust experienced in 2021, an increasing number of people are worried about the privacy and security of their online data. Security and privacy issues are extremely important in domains such as healthcare or financial services. The insurance industry is perhaps the sector most exposed to data privacy and security risks. Such issues uniqueness configure situations where the AI solutions proposed must comply with ethical and social guidelines. Models will have to be audited and insurance companies must have the responsibility of any probable incident. Maps of clear responsibilities must be generated to provide inner trust. Only solutions with a very high value added will be accepted by participants. Data access and management must follow highly restrictive regulations in order to comply with privacy requirements, cyber-related general risk policy regulations advising controls, IT operations cybersecurity responsibilities, and insurance and accounting regulations.

9.1 Data Security and Privacy

The growing reliance on the cloud for storing and processing business application data has created new and challenging problems and complexities for enterprise security, risk, and compliance teams. The same is true with cloud-based generative AI. These technologies typically require access to encrypted organizational information in order to provide an appropriate response. The use of sensitive client and corporate data presents data security and data privacy challenges, particularly for highly regulated industries, such as insurance. Cyber insurance companies are faced with the challenge of underwriting other companies' cyber insurance while being exposed to a number of security and privacy control weaknesses. Organizations in highly regulated industries require a robust privacy policy that conforms to regulatory and contractual data use obligations. For example, companies must ensure they are not violating their obligations to their customers or to privacy regulations, which prohibit vendors from using sensitive customer information for another purpose without consent.

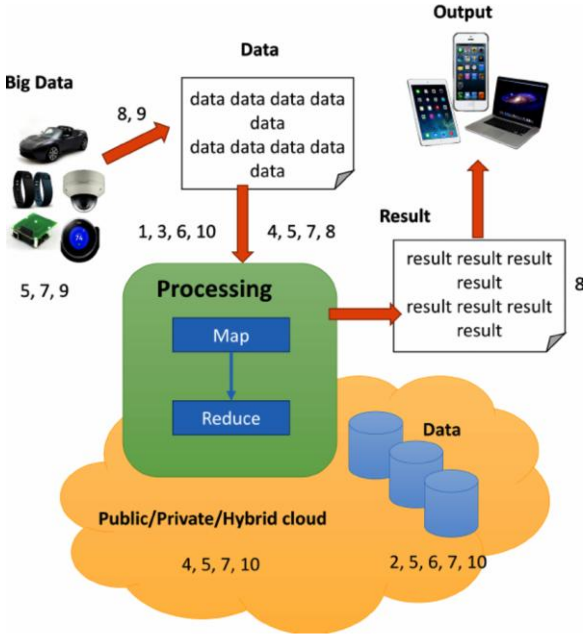

Figure 4: Security and Privacy challenges in Big Data ecosystem

Current public models typically retain user inputs, and prompt engineering to force a deterministic action takes extensive time and effort relative to the payback and repeatability for common data issues. Organizations should seek domain-specific models that are particularly well-suited for their applications or on their data, particularly those that do not deliberately retain data input. Organizations seeking to address large amounts of tedious, regularly executed requests would benefit most from these types of tools. Such models address the common business tasks organizations undergo and do so by showing a better understanding of the specific domain. The tools may initially not be able to address edge cases in the specific domain without assistance, but these edge cases can also be tuned in both those domain-specific models and the user inputs.

9.2 Regulatory Compliance

While machine learning and other artificial intelligence tools hold great promise for improving the speed and accuracy of underwriting decisions, it is not without its challenges. The underwriting process must still comply with standards to ensure the continued trust of policyholders, investors, regulators, and the general public. AI must be vetted to optimize the insurance security infrastructure while adhering to standards and model laws regarding subprime lending. Even minor lapses and breaches in underwriting access controls, physical security, data integrity, or software and systems security can have major consequences for the insurance industry and wider public.

Adverse selection remains a major concern for the insurance industry, especially in hard market conditions. AI must be used to meet customer expectation for low-friction real-time decisioning without allowing an expansive funnel that fails to zip close. In order to do so, the underwriting AI engine must remain configurable and compliant against various organizational lending policies. Bluntly put, solutions that provide push-button implementation that can be rigged to any company underwriting rule will more likely get them slapped with fines and audits than actually provide automation assistance. Furthermore, many of the fairness issues with automated underwriting will come down to not just the datasets being modeled but also the performance outcomes of those models. Insurers will need to thoroughly evaluate their model performance using various performance metrics and on different protected demographic groups during the monitoring stage to prevent discriminatory model outcomes from being found.

10. Case Studies of Successful Implementations

Insurance providers are entering into partnerships with other entities to allow for rapid, clear development. With companies offering ability-based quotes while partnering with other firms to handle claims; the companies offering specialty insurance have turned toward partnership with panel firms to supplement underwriting processes and regulatory compliance. Recreational insurance's return on premium is well below the market average. Insurers that utilize external providers capable of servicing clients through the claims experience with market-beating performance will see much increased transactional deal flow and algorithmic pricing of specialty products.

The major obstacle is education, and the most prominent recreational insurers have resources devoted to rapid learning. These recall public adjusters while the airline companies drool over reducing the two seconds for cab roughdowns. As the companies researching, databasing, and utilizing claims experience and brokerage know are inundated with claims, the open question is whether the research fuel that the property insurance industry formerly squandered upon specialty insuring research will be made up at the bottom.

For property insurance companies partnering with limited regulatory expeditors, small companies, and those with fewer resources, utilizing algorithms to verify that clients of the small property firms are of acceptable risk is another possibility. Algorithmic assessment based on predictive scoring, data scrapers, or third-party bulk sales databases can help match clients against other major transactions in their markets. Currently, the mortgage industry database is coupled with credit databases but the combination still does not process a significant percentage of mortgage transactions and deals with continuous identity exposure and false negative verifications. The problem is that scientific mortgage transactions are often the trigger of property insurance quotes and specialization.

10.1 Recreational Insurance Providers

A large variety of products are offered by recreational insurance providers, who are other than market leaders, for travel and other types of insurance to meet very specific consumer needs. These policies are often written for a period of time in 1-3 years and, due to archaic manual processes involved in both underwriting and claims management, are neither efficient nor cost effective. It is a well-known secret that up to 95% of claims are approved on a straight-thru basis after minimal risk scrutiny, if any. The existing and sometimes cumbersome processes typically include several time-consuming steps that could take days to weeks to complete and consider which essentially make life of the underwriters harder than it should be as over-reliance on tools like standardization makes their jobs more frustrating and errors more likely. Without real time and objective input from unbiased decision-making engines that would ensure consistent underwriting of risks regardless of how busy the underwriters are, the paper-heavy process will lead to more problems than benefits especially in managing the growing backlog created.

Dedicated recreational insurance companies write many different policies from all types of equipment related insurances, to liability and cancellation cover, offer travel insurance for individuals traveling for business or pleasure. The decision to insure a specialized risk is generally taken in consultation with the capacities of specialist insurers. Specialist insurers decide uncertainty regarding the likely loss ratio for a particular class of business as well as the availability of sufficient stop-loss or whole account cover to absorb the overall result of their portfolio. Given the long-lapsing nature of specialty classes, the demand for retrocession cover has grown substantially in the past two decades. The increased demand for catastrophe products has also backed the growth in parametric insurances.

Figure 5: Employee Benefits with insurance

10.2 Property Insurance Companies

"Cloud-Based AI Systems for Real-Time Underwriting in Recreational and Property Insurance" explored in the previous sections the concept of real-time decision-making and support to reduce selection bias and other factors which also creates inefficiency and unprofitable underwriting, and the algorithms, systems and approaches we develop to enable successful implementation of services to support this. Monuta and Kuiper are property companies who embraced real-time decision-making and invest heavily in digital transformations including careful selection of platforms, software packages, and products to optimize service delivery, service quality, security and integrity of data and decision-making. Monuta is a funeral insurance company offering life, funeral and burial insurance. Its founders implemented similar thinking to the modern implementation in our research. Kuiper is a tech-savvy product and third-party insurance company focusing on data-driven proposition development. Together they created a proprietary cloud-based AI-driven system to enable real-time automated underwriting of property and foundation insurance. Foundation insurance provisioning in the Benelux is a good example to illustrate how multi-party access and instant decision-making mitigate fraud in "moral hazard" during disasters. Foundation damage assessment is constrained by the small size direct assessment can be done, therefore relying heavily on external assessments. In the cases where mobile services are needed, are weekend, or extending repair period fraud risk is substantial. By offering rewards on top of the third-party supported platforms, Kuiper helps emplace permanent mobile monitoring platforms to limit fraud. The services and available budget are high enough to stay ahead of competing product propositions during disasters.

11. Future Trends in AI and Cloud Computing

In the modern age, companies are continuously working hard to meet with the demanding queries of clients to remain competitive in their field. Cloud computing has facilitated the companies by providing an easy environment that connects the company systems to the giant cloud server in order to meet the growing customer needs. With the incorporation of machine learning algorithms into the business processes, organizations are thriving day by day. The combination of cloud computing and AI will keep on making growth in the company work system and make the future advanced. In the future, there will be more availability of AI tools and the understanding level of data science will also increase, facilitating the development of next-gen solutions. As a result, companies will not need any AI experts on their boards. Cloud-based AI will give a more polished experience to data scientists. Over time, cloud services will also become increasingly intelligent.

Predictive analytics is one advanced feature of cloud-based AI, where the AI model will help predict problems and solutions based on past data of people. The prediction made will not only be focused on the problem statement but also help in decision-making of the board. AI embedded in cloud solutions will focus more on data mining, data cleaning, and decision-making. Recently, there has been a significant increase in the number of AI models that require a lot of data storage and other resources. For companies, it's a difficult and expensive process to invest in all these resources for developing AI models that are in times reused as many other companies might be using them.

It is beneficial to compile all the resources in a single cloud system rather than multiple times in the individual companies. There are also large costs involved in development. The use of pre-trained and reusable AI models on a cloud storage makes the development of application simple by using these models and companies can use their time and available resources on complicated tasks or problems. Cloud-based AI will also stress a secure transfer of data to the system which will make the organizations sure of the security of their information.

11.1 Predictive Analytics

Predictive analytics is a branch of the advanced analytics discipline that uses both new and historical data to forecast activity, behavior, and trends, and to understand business challenges and optimize decision support. Predictive analytics is a mixture of predictive modeling, machine learning, artificial intelligence, and statistical modeling. Predictive analytics can be used in business, to support automated decisions for individual transactions, to anticipate future business conditions, and to detect and minimize undesirable events.

Predictive analytics aims to measure and understand customer sentiment and risk. In life and health insurance, companies are able to use these techniques to improve underwriting and pricing accuracy but, above all, to enhance binding ratios and cross- and up-sell existing portfolio products. In case an organization would like to measure the propensity of a specific customer to buy a new product or service, predictive analytics would typically be performed using logistic regression. If the task is to provide organizations with ranked customer lists that are likely to purchase a new product or service, customer segmentation for profiling or responding to individuals where the organization has very little customer data on hand, and better positioning of a new product or service, exploratory data analysis, supervised machine learning methods, tree-based and ensemble methods.

Other commercial applications of predictive analytics include sales and marketing, financial resource management, fraud detection, product development, and risk management. Predictive analytics uses historical data in three major ways: as predictors in predictive models, to group similar observations into segments that can be modeled separately.

11.2 Enhanced Customer Experience

Nagendram, Venkatesh and Gupta design cloud-based AI systems for 24/7 real-time underwriting in recreational and property insurance. The future trends identified in the analysis hold significant ramifications for improved processes and reduced costs across sectors. One of the sectors that stands to gain from these developments is insurance. Automation of underwriting is gaining traction across lines of coverage. While auto insurance has been automated for pricing for decades, other lines of coverage are beginning to explore this avenue. Homeowners, renters, and condominium insurance coverages have found that weather events, especially hurricanes and hail, affect losses.

Insurers have begun to leverage technology and available data in tandem with actuarial science and experience to assist with underwriting. Insurers have implemented predictive analytics as a learning tool that helps to identify data and other relationships to better predict loss. Predictive analytics applies those relationships to collect and analyze external industry data, and apply the conclusions to a submission. In the future, underwriting will require the application of enhanced customer service principles to the collection of underwriting information. This paper provides an overview of how cloud-based technologies and artificial intelligence can enhance operations and customer service in the insurance underwriting process.

Customer experience will benefit from cloud-based AI in two different ways: technology managing the underlying business processes that turn around an underwriting decision, and technology utilized at the customer interaction interface. To the first point, a cloud-based AI platform has the inherent capability to speed up the back-end processes that escort a transaction, and utilize conditional logic to determine what decisions will be needed based on various customer responses. For example, the need to coordinate interaction between the customer and the underwriting department is eliminated as real-time information delivery to the customer can be anticipated. Automating the quote generation process can handle many customer decisions.

12. Ethical Considerations in AI Underwriting

Algorithmic underwriting generally, and Smart Underwriting specifically, use AI technology in multiple ways to collect, interpret and assess information, and then make an inference or recommendation about a matter of great consequence to an applicant or party affected by a decision. As in all AI systems, ethical considerations are paramount. Important decisions with great impact, involving people's lives as well as the potential for discrimination, inequality, and lack of fairness in substantive content and process, must always be considered upfront. Decisions about whether and when to use a Smart Underwriting tool must not only take such factors into account, but must be considered openly and transparently. To that end, needed materials, models, and procedures must be available for internal and external evaluation.

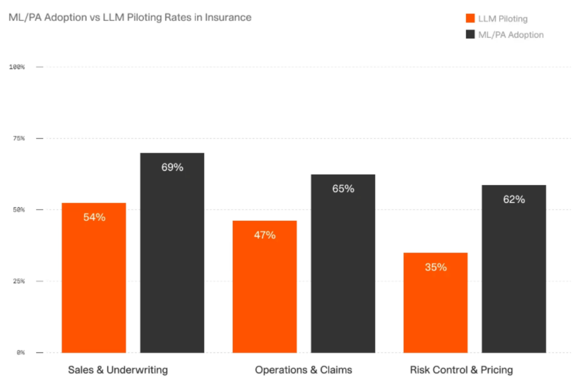

Figure: AI for Insurance Underwriting

There are several key issues relevant regarding SmartUnderwriting and its implementation in these areas. Algorithmic bias is a central concern – understanding the risk that algorithms replicate, enhance or generate their own formulaic bias against protected classes such as people with disabilities, women and minorities. Predictive models must incorporate fairness constraints to ensure that underlying population disparities are not exacerbated. Transparency of algorithmic decision-making is also important. Individuals adversely affected by the processing of information using an algorithmic system must have a way to access the basis of its decision and the rationale behind it, as well as the criteria and data used to process the information and make a recommendation or prediction. What follows provides an overview of key points regarding these and related issues as they apply to SmartUnderwriting.

12.1 Bias in Algorithms

Cloud AI systems are trained on data that has already been gathered about subjects, so there will likely be some bias embedded in the data. Data can overshadow any bias in the algorithm when coming to a decision. For example, a hiring algorithm reserved for use in a specific company may be required to undergo audits to ensure that it is not biased against protected classes within the company. However, whether an algorithm should be made open to scrutiny, or the underlying data revealed where it became clear some bias was inside the data, is a question that does not have a straightforward answer. One possible suggestion to alleviate the issue is to dummy code categorical data to disallow the possibility of bias decisions. High-level AI systems used for decision-making may also inadvertently bring bias into a decision process where it was not desired. As an example, an AI system meant to determine people's sexual orientations based on their social media accounts was found to have incorrectly predicted a gay sexual orientation with a high probability in a significant percentage of men who were in fact gay when tested on actual gay men. Problematically, while correctly classifying a high percentage of men who are not gay, the potential negative impact of biased decisions becomes clear. The analysis system assumed the orientation of individuals from a diverse range of places around the world based only on social media elements like profile descriptions and account data. These results show that AI systems may unintentionally discriminate against certain groups. Balancing AI evolution by utilizing data and being aware of society will remain difficult. However, as people learn more about AI systems and their potentialities, companies may need to become more involved in support of ethical considerations and be aware of bias characteristics related to their product usage.

12.2 Transparency in Decision-Making

As the tide turns against the principle of maximizing shareholder value at the sole expense of other stakeholders, business firms are being subjected to greater scrutiny regarding how they carry out their work. Public companies are providing additional disclosures in areas concerning environmental sustainability, diversity inclusion, and supply chain management. Implicit in these reporting requirements is the question of how these firms make the key decisions that lead to the financial and operational successes or failures of the firm and its stakeholders: the employees, customers, suppliers, communities in which the firm operates, and the shareholders. For its AI systems, a firm might implement or adopt an explainability or transparency protocol. Simple and clear logic rules might be implemented to assure stakeholders that the right decision is being made. If certain underwriting risk decisions are easily communicated and explained, this can provide stakeholders with some level of assurance that the life insurance AI tools make the appropriate decision, based on a clear set of understandable guidelines.

Helping underwriters to better understand models would seem to aid understanding in every way. The underwriters themselves are the experts in risk assessment and would know a least a few of those most plausible risk model explanations. It could enable decision-makers to better decide whether they need to have any one data verification, search for additional data, validate models against other tools, or rely less on these more sophisticated underwriting AI models. Such implementations could also help in discussions with other stakeholders in discussions about the most relevant risk factor explanations for the underwriting decisions being made by all five systems.

13. Conclusion

Some may say that artificial intelligence has been overhyped, a bubble waiting to burst for decades, and that, in fact, AI is only a probabilistic engine. The same may be said about neural networks or, more recently, deep neural networks. In the context of property and casualty underwriting, they have been employed in a tiny fraction of the potential markets and layers of use of the huge network of interconnected processes, potentially generating significant savings to insurers and significantly lower premiums to the insured. Nonetheless, while proposing the framework for real-time cloud-based underwriting has been simple, getting to this moment has not been straightforward.

Many items previously identified as weaknesses of AI applications are but growing pains. Some models, like neural inference networks and more recently one-shot learning models, thus developed to minimize the training data deficit, are already in the research pillar of AI. Others are yet to be created to deal with the fact that property and recreational casualty are a higher order stochastic process, but primitive applications are already out there. All that remains now is the democratization of technology: providing insurance techs, brokers, and carriers with cloud-based simple interfaces able to connect data and systems and prepare companies to act with an open-mindedness toward a new relation with their clients – assume risks based on what makes them unique and not based on what they have in common – and promote the humanization of data. Consistent after-sale support is of utmost importance to those for whom AI is a new solution.

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