NAIC National Association of Insurance Commissioners & The Center for Insurance Policy and Research
CIPR newsletter

Intelligent Machines and the Transformation of Insurance

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◆ Introduction

The history of intelligent machines is punctuated by bold predictions regarding their potential, as well as admonitions about their limitations. Traditional computing is rules-based and dependent on organized information and external programming. However, the science of artificial intelligence (AI) is dedicated to making machines intelligent by allowing them to learn independently from disparate and varied data.

Machine learning, which at its core is how AI can be achieved, is the act of teaching machines to learn from their experiences and adapt to their environment. In effect, machines can be self-taught to replicate the multilayered complexity of human behavior, ostensibly without any faults, weaknesses or hesitation.

The ability of AI and machine learning to automate and optimize every business function has been a game-changer for all industries. The insurance industry is no exception. In fact, being a historically data-heavy industry, it has always strived to improve its analytic capabilities with the latest technological tools.

Machine learning and AI seem to be tailor-made for the insurance industry with a variety of applications already widely adopted. Most obvious applications of machine learning in this industry are in claims processing, underwriting, fraud detection and customer service. Insurers also expect benefits from the analysis of competitor actions, customer trends and the detection of patterns in the data to gain unique insights at a detail and speed impossible for humans.

Although these new technologies are transformative in nature, they also present certain challenges just like other historical technological revolutions. This article briefly discusses how machine learning works, explores its main insurance applications and considers regulatory concerns. For a closer examination of how machines truly learn, their immense analytical capabilities and the implications for the insurance industry, the NAIC Center for Insurance Policy and Research (CIPR) is working on a research study, *The ABCs of Machine Learning*, which will be released in 2019.

◆ Machine Learning Basics

Machine learning is considered a subset of AI. While AI includes the entirety of computer systems able to perform complex tasks normally requiring human intelligence, machine learning involves programs that have not been explicitly entered into a computer. Machine learning is the capability of computers to acquire their own knowledge by extracting patterns from raw data.[1] This is distinct from other types of AI systems, which work by hard coding already acquired knowledge.

Machine learning has become the leading solution to most classic challenges with AI. Machine learning dominates the fields of computer vision, speech recognition, computer dialogue systems and robotics.[2] Interestingly, it borrows heavily from neuroscience to build algorithms based on artificial neural networks mimicking human brain processes of learning. Artificial neural networks, like their biological counterparts, are arranged in layers with information passing from one layer to another.

In this layered structure of algorithms, there are input and output layers with hidden layers between them. It is in the hidden layers where the artificial neurons process the inputs to produce an output similar to the activity in the human brain. Networks with multiple hidden layers, referred to as deep networks, allow for the processing of larger and more complex data and more computationally intensive training. Deep artificial neural networks are behind deep learning, which is a subset of machine learning.

The development of artificial neural networks would not have been possible without advanced computing power and big data. These artificial neural networks are powered by an enormous amount of information in order to learn. Recent innovations, such as self-driving cars, Alexa/Siri and Facebook's facial recognition owe their existence to machine learning technologies like artificial neural networks.

◆ Machine Intelligence in Insurance

For most of their history, insurers have depended on expert judgments and simple rule-based heuristics to make critical predictions. Insurers have leveraged these new quantitative and computational technological innovations to improve their predictive modeling. However, the extensive use of data for business process optimization and evidence-based decision making has not yet been as prevalent.

Although data has always played a central role in the insurance industry, most insurers are processing just 10–15% of the data they possess.[3] Given the volume and richness of the data insurers have at their disposal, there is still so much value to be tapped. Machine learning is used to effectively mine all available data for predictive analytics and business insights.

Despite the mounting interest in machine learning, the number of insurers deploying machine learning still remains

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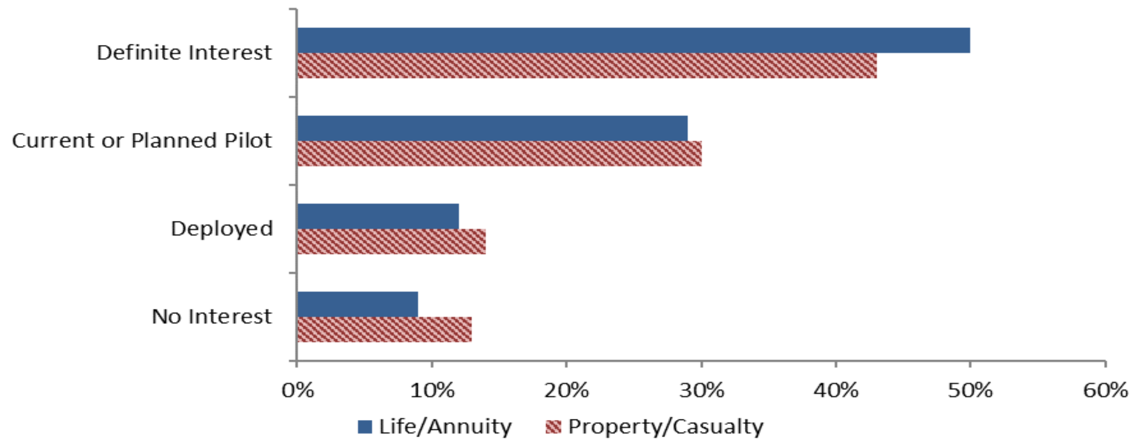
FIGURE 1: INSURER MACHINE LEARNING ADOPTION



Source: Novarica.

relatively small.[4] According to Novarica, only 14% of property/casualty (P/C) insurers and 12% of life insurers actively use machine learning. However, about 30% of all insurers are working or plan to work on pilot programs, and nearly half are interested in developing machine learning (Figure 1)[5].

According to a recent report by Earnix, from all of the insurers currently using machine learning, 70% employ it to develop risk models, 45% to create demand models and 36% for fraud detection (Figure 2)[6]. These numbers are significantly ahead of the banking industry, in which only 11% of banks have embraced AI technologies.[7]

Many insurers report the process of adopting machine learning entails steep learning curves. In fact, 82% of insurers indicate they are still novices (30%) or have intermediate knowledge (52%) in developing and applying machine learning. Only 14% of insurers consider their use of machine learning as advanced, and just 4% feel they are experts.[8]

Despite the learning curve, those insurers who have adopted machine learning report positive returns on their investments.[9] About 52% of insurers expect immediate benefits mainly in terms of greater analytical accuracy and cost sav-

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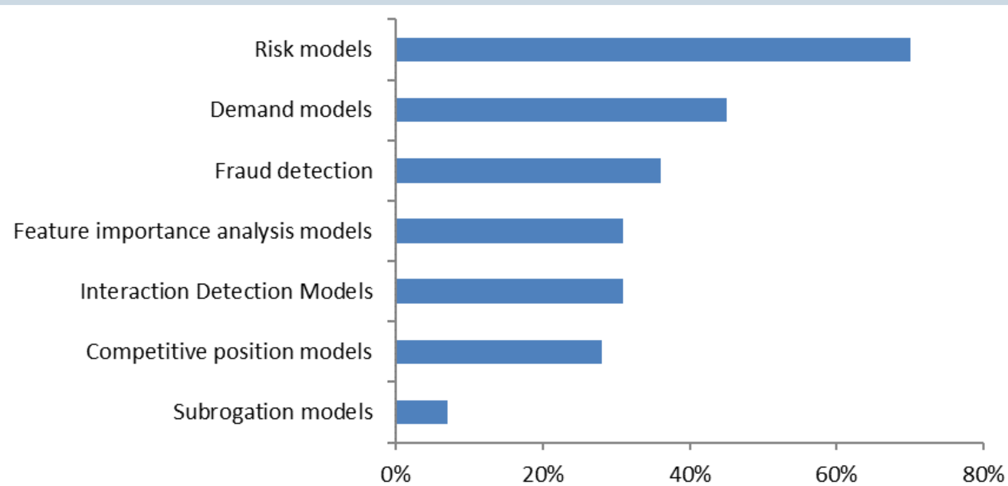
FIGURE 2: TYPES OF MODELS CREATED WITH MACHINE LEARNING



Source: Earnix.

ings (Figure 3).[10] However, benefits of machine learning tend to accrue unevenly with larger insurers being the main beneficiaries.

Many insurance technology start-ups ("InsurTechs") are concentrating their innovation efforts on developing machine learning to help bring new AI-enabled applications into the insurance market. From all leading innovations among InsurTechs, the use of big data with machine learning tops the list.[11] According to a survey by International Business Machines (IBM), more than 50% of InsurTechs use AI and machine learning.[12] Leading insurers see InsurTechs as key drivers of innovation and, therefore, ideal sandboxes in which to experiment with AI and machine learning technologies. About 45% of all insurers and 81% of leading insurers have invested in or work closely with one or more InsurTechs.[13]

◆ FRAUD DETECTION

Insurers are primarily using machine learning to optimize traditional insurance functions. This includes the growing problem of insurance fraud. According to various estimates, annual insurer losses from fraud range from $30 billion to $80 billion.[14,15] Fraudulent claims represent a significant cost, but it is expensive to identify fraud the way claims are currently processed. By leveraging AI and machine learning, insurers have developed tools capable of sifting through all the claims to detect patterns of possible fraudulent activity.

Machine learning algorithms are superior to conventional statistical predictive models for fraud detection because they can quickly scan enormous amounts of unstructured data in different formats. This includes claims adjusters' handwritten notes, repair estimate documents and claimants' social media accounts. It can even sift through videos and images to identify potential fraud.

The main advantage of machine learning is the ability to discover new variations of known and new fraud patterns. Obvious patterns have always been quite clear for investigators to spot, but many data anomalies may suggest fraudulent behavior that can be virtually undetectable by humans. With machine learning data analysis, human behavior can be analyzed at much deeper levels to produce incredibly precise criteria. The ability to continuously learn from data to detect new anomalies and patterns makes machine learning a uniquely powerful tool for fraud detection.

Machine learning has allowed investigators to prioritize claims and specifically target only those already red-flagged as likely fraudulent. The benefits of employing machine learning for fraud detection are three-fold. First, insurers can significantly reduce their overall losses from fraud. Second, insurers can use their investigative resources more efficiently. Lastly, insurers can avoid adversarial customer interactions by not challenging innocent claims.

◆ CLAIMS PROCESSING

Integrated with fraud-detecting solutions, machine learning can also be used to optimize claims processing. The interaction between the insurer and the policyholder and the ease and speed by which a claim is settled drives, to a large degree, both customer satisfaction and loyalty. Simplifying a stressful process for customers through claim process auto-

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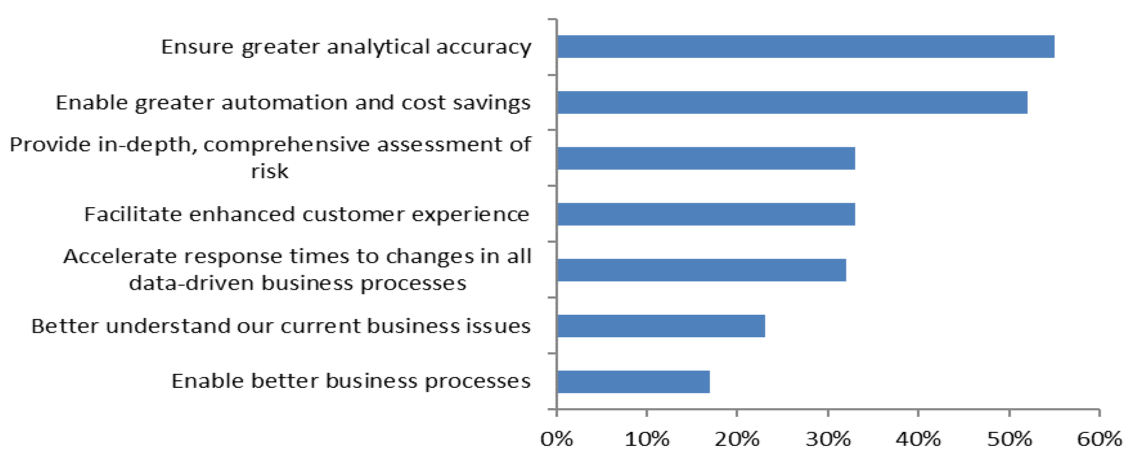
FIGURE 3: TOP BENEFITS REALIZED WITH MACHINE LEARNING



Source: Earnix.

mation can enhance customer experience while reducing settlement time and cutting costs.

Machine learning can allow computers to communicate with customers via phone call or email, using speech recognition and text scanning, and automatically fill out a claim. Machine learning can decrease the volume of calls and inquiries during the claims process, eliminating costly human errors that are often unavoidable in manually intensive tasks. An automated claims process can take only minutes to complete instead of the industry typical 72 hours.[16]

Better predictive models powered by machine learning can help insurers better understand and manage their claims costs. Gained valuable insights can save millions of dollars in costs through proactive claim management and fast claim settlement. Insurers can also calculate how much funding they need to allocate to claim reserves with more confidence and certainty.

InsurTech start-ups leading the digitalization of the industry exclusively use chatbots to interact with their policyholders during their claims process. Claims are submitted through apps on a mobile phone or computer, and they are usually approved within minutes.[17] The policyholder is then notified when the payment is made. Thus, AI and machine learning can effectively and efficiently take care of every step of the process from first reporting the claim to settling it.

◆ UNDERWRITING

Insurers have to evaluate a multitude of highly complex and often new and unfamiliar risks in the process of underwriting. In addition, there are multiple sources of useful data that can provide insights into a variety of risks. However, managing such large amounts of data is becoming challenging and often impossible for underwriters.

By incorporating real-time, highly granular data, machine learning can help underwriters simplify the complexity of their work and improve their decision making. Machine learning applications learn from training sets of past experiences to highlight key considerations for human decision-makers and minimize errors.

An underwriter's assessment can be flawed if false information is used or vital information is missing. This would essentially invalidate the essence of the underwriting process. Machine learning can verify the accuracy of the information applicants provide and reveal even more information using diverse sources like social media, news media and government agencies. In property and casualty insurance, machine learning can use data from digital maps and high-resolution aerial imagery from drones and satellites to identify property features and quickly assess risks.

Machine learning can maximize the benefit from the explosion of data available to insurers from connected devices in homes, cars and even on people with wearables. In such a data-rich environment, personalized pricing in real time can be possible with machine learning. The increasing penetration of devices such as fitness trackers suggests underwriters could accurately calculate a policyholder's personal risk score based on daily activities, as well as the probability and severity of potential events. With pricing available in real time based on dynamic data from usage and behavior, policyholders can make decisions regarding their actions and how they affect their insurability, coverage and premiums.

◆ SALES AND MARKETING

The benefits of developing AI and machine learning capabilities in sales and marketing are evident. More than 85% of all customer interactions are predicted to be conducted without any human involvement by 2020.[18] Insurance consumers are increasingly expecting highly personalized services preferably through a digital medium, such as a smartphone. Machine learning can provide such customized experiences for consumers. It can also extract valuable insights from vast amounts of data on demographics, personal preferences and lifestyle generated during these interactions. Insurers can then use the data to develop personalized offers, policies and loyalty programs for their policyholders and prospective customers.

By increasing their touch points or interactions with customers, insurers can develop a mutually beneficial long-term relationship with them. With machine learning insurers can estimate the lifetime value of their customers. This value is represented by the difference between the revenues gained and the expenses made projected into the future relationship with a customer.

Lifetime value is calculated with behavior-based models widely applied to forecast customer market preferences and retention. Machine learning algorithms process available customer data to estimate risk probabilities from behaviors and attitudes, and the likelihood of keeping or surrendering policies. Customer life value prediction enhances insurers' marketing strategy development with machine learning providing valuable consumer insights.

Machine learning algorithms can also classify consumers based on their individual attributes such as education level,

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profession, income level, age, location, etc. Consumer segmentation based on personal information and characteristics can allow for more precise targeted marketing for specific policies tailored to the perceived needs of each segment.

◆ Risk Management

Complex algorithms and machine learning-based systems are used to define and achieve organizational goals, accelerate performance, and improve differentiation. Risks to growth and profitability can be quantified and analyzed, especially those considered blind spots, as they are generally unknown to management.

The complexity of machine learning brings transparency concerns. In terms of risk management, there is a need for appropriate controls to be in place to manage machine learning as a tool and as a technology. The algorithms can evolve beyond even the understanding of those that created them. As the data gets reshuffled and combined in different ways with other data, it is important to be aware of new risks with these algorithms and the conclusions they provide.

Input data may also be vulnerable to risks. For instance, the data used for training in machine learning could have biases. The data may also be incomplete, outdated or at times entirely irrelevant. There could also be a mismatch between the training data and the actual input data used to generate the output.[19]

Decisions regarding the output are also vulnerable to various risks, such as erroneous interpretation or inappropriate use of the output. Algorithmic risks can potentially have more broad and long-term implications for an array of insurer risks, including financial, operational, market and reputational. Insurers should be aware of algorithmic risks when they develop and deploy machine learning solutions to ensure they are appropriately and effectively managed.[20]

◆ Regulatory Challenges

The independent learning nature of machine learning raises concerns for state insurance regulators. With machines capable of learning how to improve independently and without any human involvement, it is important to ensure the deployment of machine learning continues to adhere to regulations regarding data privacy, fairness, discrimination and cybersecurity.

Machine learning algorithms are based on proprietary data and models particularly difficult or impossible to interpret or explain. The resulting "black box" poses challenges to state insurance regulators trying to understand what data is used, from what sources, and how the machines actually reach their conclusions. This lack of interpretability and auditability could potentially embed unknown and unforeseen risks if this technology is not appropriately managed and supervised. For this reason, the Financial Stability Board (FSB) cautioned the widespread use of machine learning models could become a macro-level risk for the insurance market.[21] Adequate testing and training of machine learning tools, auditable by regulators, is essential to ensure they operate within their design parameters and in full compliance with existing regulations.

The ability of machine learning to analyze data at a very granular level for more accurate pricing and risk assessment could have consumer protection implications. To avoid discrimination, data on sensitive characteristics such as race, religion, gender, etc. are not supposed to be considered by insurers. However, machine learning algorithms may use geographical data or other individual attributes, creating outcomes which implicitly correlate with those sensitive characteristics. This could result in the same biases and exclusions of groups of consumers regulators were trying to avoid in the first place.

By using machine learning applications to price risk, insurers could reduce the degree of moral hazard and adverse selection they are facing, but at the same time undermine the risk pooling function of insurance. It is true offering dynamic personal coverage with continuous pricing adjustments according to policyholders' changing circumstances and behavior could solve the moral hazard problem. It is equally true offering highly customizable policies reflecting the unique characteristics of each individual would eliminate adverse selection. However, this type of risk pricing would lead to higher premiums for riskier consumers, potentially rendering certain groups of people effectively uninsurable by the private market.

In addition, the more dynamic and adaptable machine learning programs become, the harder it is to predict their actions and their impact creating new risks, often with a distinct ethical dimension. A set of ethical guidelines for data scientists developing machine learning applications is needed to ensure their actions do not harm consumers and the public in general. The Code of Ethics of the Association for Computing Machinery (ACM) currently serves as the basis for ethical decision-making by its members.[22] It supports accountability and transparency as the most effective means to ensure compliance with developers' primary responsibility which is to always protect the public.[23]

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Collecting data from diverse sources to arrive at automated conclusions and decisions about people raises a host of questions about privacy and data quality. Insurers should be able to show what inputs go into their models and explain the logic behind their decisions. At the same time, with machine learning, this kind of transparency into the data and the decision-making process tends to be more difficult than traditional rules-based models. New regulatory approaches may be required to effectively alleviate concerns about machine learning models.

◆ CONCLUSION

AI and machine learning are developing technologies with broad uses and high utility for insurers. Measuring, controlling and pricing risk with greater precision can reduce costs and improve efficiency for insurers and some consumers. While machine learning can engage and empower consumers and even in some cases expand insurability, it may potentially price other consumers out of the market.

Efforts to improve the interpretability of AI and machine learning are important for insurer risk management, effective regulatory supervision and greater public trust. Insurers are innovating and changing the way insurance is delivered, purchased and experienced. State insurance regulators are responding by broadening their regulatory scope to account for all the challenges created by these new innovations. The state insurance regulatory framework strives to be forward-looking and sufficiently flexible to allow for innovation, without straying from its mission to protect consumers and the viability of the insurance market.

ABOUT THE AUTHOR

Dimitris Karapiperis joined the NAIC in 2001 and he is a researcher with the NAIC Center for Insurance Policy and Research. He has worked for more than 20 years as an economist and analyst in the financial services industry, focusing on economic, financial market and insurance industry trends and developments.

Karapiperis studied economics and finance at Rutgers University and the New School for Social Research, and he developed an extensive research background while working in the public and private sector.

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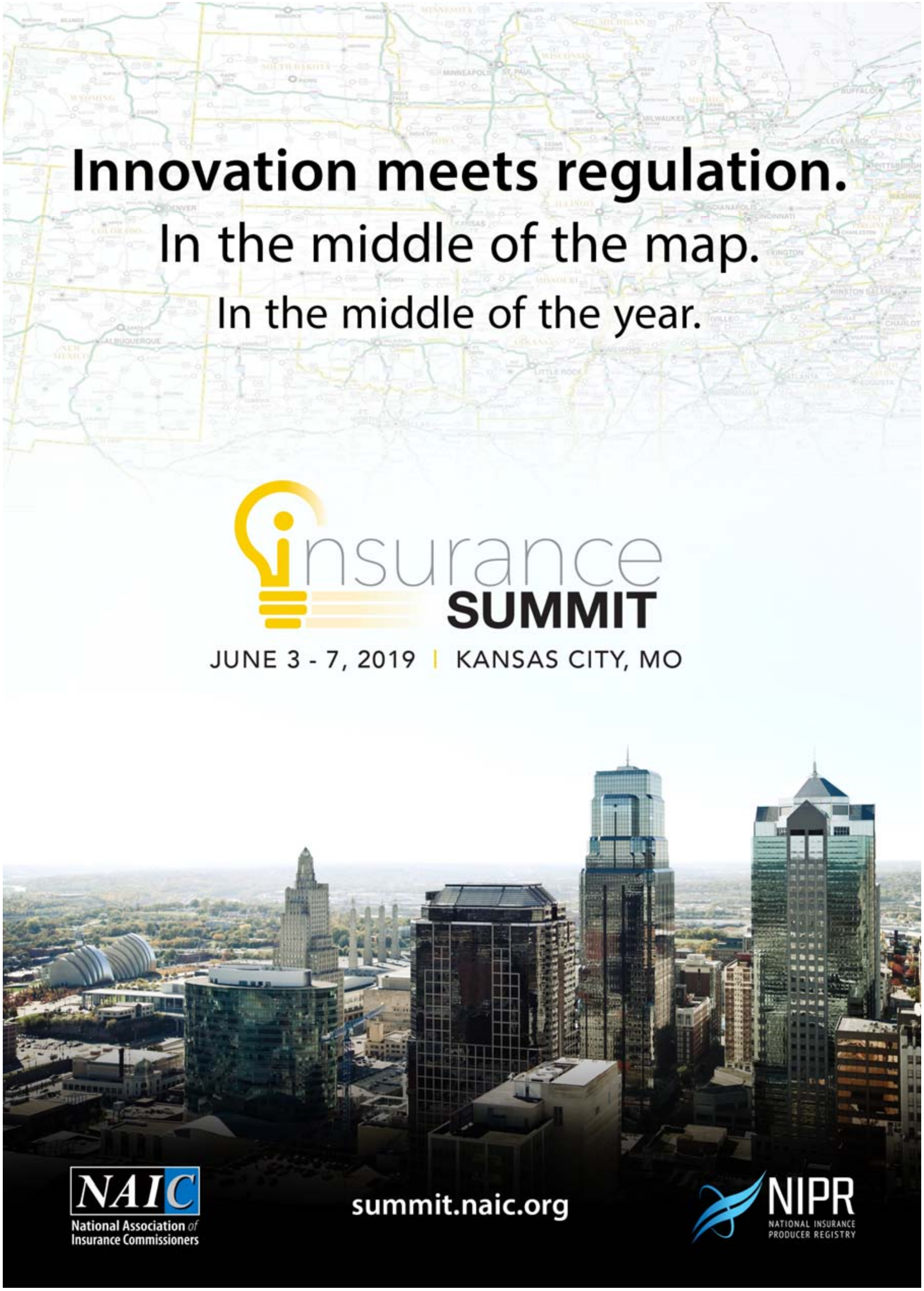
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