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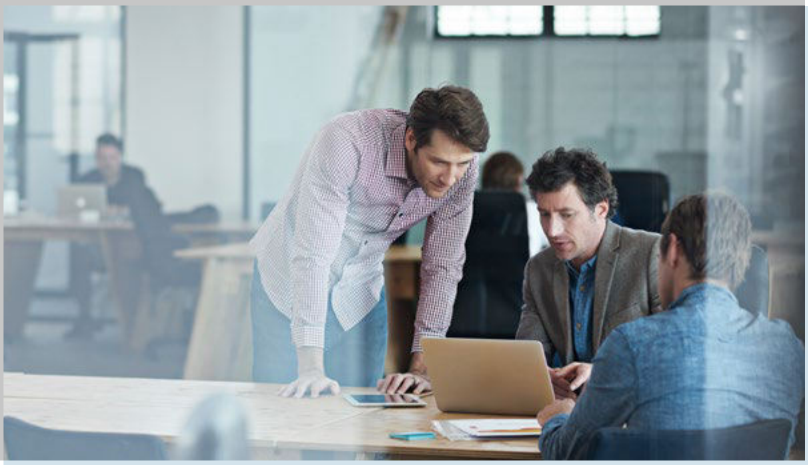
Insurance: Models, Digitalization, and Data Science



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Abstract. This article summarizes the main topics and findings from the Swiss Risk and Insurance Forum 2018. That event gathered experts from academia, insurance industry, regulatory bodies, and consulting companies to discuss the challenges arising from the impact of data science and, more generally, of digitalization to the insurance sector.

1. Introduction

One of the dominant topics in our times is how the exploitation of an ever-increasing amount of data with a growing amount of computing power and analytics tools will reshape our environment. Indeed, the capabilities of computers today have turned data science – the science of extracting knowledge or insights from data – into one of the most promising and radically new directions in virtually all business sectors. At the same time, other digital technologies, most prominently block chain, are being hailed as having the potential to revolutionize the way business is done. After a hesitant start, the digital transformation of the insurance industry is now rapidly gaining momentum.

The digital transformation has the potential to affect all components of the insurer's value chain: products $\rightarrow$ marketing $\rightarrow$ underwriting/pricing $\rightarrow$ distribution $\rightarrow$ claims $\rightarrow$ services (McKinsey, 2016a; Eling and Lehman, 2018). For example, products are likely to become more personalized and usage based. Personalized mobile and online channels may replace traditional marketing instruments. Rich customer data and real time analytics will allow usage- and behavior-based pricing and underwriting and traditional distribution channels may be replaced or complemented by online distribution but also by InsurTech start-ups such as Lemonade. With the right tools for fraud prevention, certain claims adjustments can be apt to for automation. Finally, from their experience with other sectors in which they can interact with service providers in a seamless way via their electronic devices, customers have also come to expect a similar experience when it comes to the services provided by insurers.

At the same time, these developments can increase competition and put pressure on the insurer's margins. In such an environment, the competitive pressure will force insurers to achieve greater operational efficiency overall. Here, digitalization can help to streamline processes and to eliminate redundancies in an industry that has not been too agile in reacting to change in the past. Ultimately, these developments may result in a reassessment of the skills required of the workforce and affect the way in which insurance companies are organized.

This 2018 edition of the Swiss Risk and Insurance Forum was devoted to critically explore the various aspects of data science on insurance. As was the case with past editions of the event, the idea was to have a group of individuals with different kinds of expertise address a host of questions relating to the general topic of the conference. In particular, the objective of this edition was to increase our understanding of the technological, business, legal and ethical aspects of the integration of data science techniques in insurance activities and of the challenges that go along with it.

In this paper, we summarize the main findings and discussions. The conference was not aimed at generating common positions and, as a result, this summary does not necessarily reflect the views of all participants of the workshop and the inclusion or omission of certain aspects is the sole responsibility of the present authors. This was the fourth edition of the Swiss Risk and Insurance Forum and summaries of the previous editions can be found in Albrecher et al. (2016), (2018), and Koch-Medina et al. (2014).

The structure of the paper follows that of the conference which was structured along the three conceptual blocks: Methods and models, Business cases, and Data availability, Protection, and Regulation.

2. Methods and Models

The arrival of new data affects the whole insurance value chain, from customer acquisition to claim settlement. Actuaries have been using simple forms of supervised statistical learning for years. To price motor or home insurance for example, they often rely on statistical methods such as the generalized linear models (GLM) or the generalized additive models (Ohlsson and Johansson, 2010). In their book on statistical learning for actuaries, Denuit et al. (2019) identify three main types of approaches: GLMs and their extensions, tree-based methods, as well as neural networks and unsupervised learning.

Nowadays, only a few insurers and reinsurers are really using pure data analytics on a large scale and applications are often limited to some promising lab applications. In the academic literature there are, for instance, some use cases of telematics data (Verbelen et al, 2018; Ayuso et al, 2016; Guillen et al, 2018) and individual data-based reserving (Baudry and Robert, 2017), as well as use of OCR (optical character recognition) and natural language processing to analyse legal, claim-related documents or reinsurance treaties. Many insurtech start-ups ambition to automate customer underwriting and intermediation, as well as claim management and fraud detection. One natural question is whether those technologies can get out of the lab and be launched on a broad scale. Which governance process should be put in place for such innovations? In this chapter we describe some methods and models that are often used in the insurance industry and we discuss the governance process and the associated challenges.

In terms of pricing, actuaries have traditionally been using risk factors like the age of the policyholder, the age of the policy, the policyholder's address and occupation, experienced claim history, the type of insurance package (e.g., level of guarantee, face amount deductible), some information on cross-selling, as well as some features that depend on the line of business. For example, in motor insurance, relevant additional features include the power and the type of car. The current challenge consists in designing and applying effective regression techniques to find an appropriate function that links response variables like the number of claims, the yearly aggregated claim cost, or the remaining time up to the next policyholder event (e.g., claim, lapse) with a highly increasing number of features that include traditional ones and new ones – like telematics data, data coming from the Internet of Things, as well as web-based data, including the purchasing strategy of the customer during the acquisition process. One must take into account selection effects: Some variable could be considered as useless for customer acquisition and pricing by machine learning algorithms; however, removing the question about this variable from the underwriting process could breed huge losses due to adverse selection. Besides, insurance data is censored in complicated ways, due to deductibles and limits in P&C insurance, or due to censored individual policyholder histories in life and health insurance (Lopez et al, 2016) . Some policyholders may not report some claims due to bonus hunger, and some lines of business suffer from non-stationarity coming from inflation or developing long-term trends (e.g., longevity or long-term care).

Starting from GLM's, the link function may be enriched by adding various types of terms. It may also be estimated. Several scores may be included. One may also replace the response with its gradient, hoping to speed up computations.

Classification and regression trees have been regularly used by actuaries to price contracts and to analyze lapse risk for example. In random forests, data points and predictors are randomized and results are averaged over a large number of random trees.

Unsupervised learning is already used in practice in fields that can be useful for the insurance value chain like image and video processing and pattern recognition, emotion and voice recognition, or drug repositioning. It could be used in the future to digitize some paper documents, to provide online guidance for the client manager regarding the emotions of the customer and to select the right advisor, or to refine targeted prevention in life and health insurance.

The emotions of the customer during a phone or video conversation, the data collected by wearables and other connected devices and many other types of data may become available, leading to the development of new credibility models enriched with data of very different formats. Risk monitoring and early monitoring systems are needed to protect populations and mitigate claims arising from disasters like heavy rainfalls, to save lives thanks to wearables in personalized health or to detect the non-validity of actuarial assumptions fast enough (El Karoui et al, 2017).

In P&C insurance, traditional claim reserving methods are based on aggregated data: claim development triangles. Summarizing the tremendous information about claims into one triangle has of course many drawbacks, including lack of robustness and propagation of errors. It also simply discards very useful pieces of information of different formats. Recently, Wüthrich (2018) used machine learning techniques (CART) to predict the number of RBNS payments. Baudry and Robert (2018) use some other machine learning methods (including the so-called ExtraTrees algorithm). Their prediction flow is able to compute RBNS and IBNR reserves separately, run the full reserving process as of any date as required (e.g. via backtesting, compute reserves along any time granularity, learn from any subsample of historical data specified by user and learn from any subspace of features specified by the user. In their paper however, their method is tested on simulated data.

This is the problem pointed out by many insurers: “we know that the data exists, but we cannot access it!”. Data privacy and data availability remain potential obstacles for insurers. For example, raw telematics data is very seldom collected by the insurer. A tech firm receives the data from the device and provides some summarized data to the insurer (number of traffic violations, number of near-collisions, mileage and driving time on each type of road, for each phase of the day, for each type of weather condition, …). In addition, and independently from data privacy concerns that are further discussed in the sequel, it is necessary to minimize collected and processed data in a smart way. However, the insurer too often needs to rely on a third party to perform this crucial data minimization process and risks to be marginalized from the insurance value chain.

Another area of data science is outlier detection. This has been used for several years for credit card fraud detection. It is very promising in insurance and can be combined with image and video processing by human-machine collaboration: right after the claim, some start-ups propose some interface for the policyholder to take pictures of what just happened. In fact, even with machine learning, studies have shown that the mere fact to ask the policyholder to record a video where she explains the claim significantly reduces fraud risk, as customers are more reluctant to lie on video than on the phone. Besides, assistance and replacement services may now involve sensors placed into the car or into the phone: if something happens, the device is geo-localized, the insurer can automatically help by providing assistance to the driver or order a new phone glass to be delivered at the policyholder’s door. In addition to the service provided, this innovation is likely to reduce fraud risk. Outlier detection also enables reinsurers to detect any unusual sentence in their reinsurance treaties that could be dangerous for their risk exposure.

This evolution requires sound risk management, validation procedures and oversight. Should they differ from classical model validation processes? In a recent study, the German insurance and bank regulator BaFin (2018) made the following statements for the insurance industry:

- Neither humans nor algorithms should be able to do whatever they want without oversight by people being personally responsible.
- Algorithmic decision-making processes should not be used without having appropriate additional extended checks.
- Market structures are changing and new systemic risks are on the rise.
- Protect consumers against extreme forms of dynamic pricing.
- Even with more effective forms of selections, consumers should have access to needed solutions and discrimination has to be avoided.
- Consumers should always have the possibility to choose whether they want to provide personal data for a service or not.

Discrimination aspects and consumer protection will be discussed in the next chapters. Regarding machine learning validation, BaFin (2018) seems to regard it as any other form of actuarial tool: the chief actuary should give an opinion on the appropriateness of the actuarial assumptions and methods used, whatever they are. Will actuaries only be validators of blackbox approaches? How can we compare the performance of humans with those of machines? Accuracy is not the only criterion. One may use some economic criterion to assess performance, and even to modify the design of the estimation algorithm. An interesting point regarding model validation is that humans tend to be less forgiving for mistakes made by machines than for the human ones.

During the discussion, some participants claimed that actuarial models would become a new type of commodity. Some others mentioned that the most recent developments of machine learning tried to combine human experience with machine learning. Actuaries could have a key role in data selection and minimization, in setting goals and managing ethical and reputational risks. Besides, in most methods, from Extreme Gradient Boosting techniques for lapse rates prediction to Kohonen maps for policyholders clustering and health prevention program development, expert judgment is needed: parameters need to be chosen or fine-tuned, bagging, boosting and other methods must be optimized, the initialization of algorithm and the order of operations often plays an important role, and the final output is still much better if a human being cooperates with the machine. In terms of model validation, actuaries should be involved to prevent overfitting, check robustness and favor interpretability.

In terms of risk management, one must take into account the fact that any risk measure ceases to be a good risk measure as soon as it becomes a target (Goodhart's law). Therefore, as soon as policyholders will understand that they are observed and monitored by the insurer, they will adapt and modify their behavior. Machine learning techniques may be able to adapt to changing behaviors if it is possible to learn quickly enough. However, in presence of classical governance rules for underwriting, companies may face new risks due to policyholder adaptation and collaboration thanks to social networks.

New systemic risks may arise, in particular the risk of default of a key provider in case of monopoly. Besides, model risk, reputational risk and competition are expected to rise. Lower margins will be less forgiving for claim variability and bad surprises. The development of multi-channel offers is likely to induce lower retentions and more market instability. Solvency and systemic risk management will need to be revisited by regulators.

3. Business cases

The potential for digitalization to change the way the insurance business is conducted is huge. Applications range from enhancing process efficiency, through improving product development and underwriting, to redesigning distribution strategies and customer interactions as well as business models. At the same time, digital capabilities lower the barrier for new entrants – also non-insurers – to take possession of parts of the insurer's value chain.

One of the areas that has been the focus of artificial intelligence applications in virtually all business sectors is the personalization of the interaction with customers, including the personalization of product offerings. Traditionally insurance companies have been strong at selling insurance but not necessarily in cultivating customer relations after the initial sell. Today this seems untenable as customers extrapolate from their experience with other product and service providers and come to demand similar experiences from insurers. Indeed, cultivating customer relations and customer ownership will be a key battle field on which incumbent companies and newcomers will fight to gain access to and to keep profitable business. Next to technical underwriting skills, superior products and services will be the critical success factors (McKinsey 2017).

One expectation of today's clients is to be able to deal quickly and on a 24/7 basis with certain standard concerns such as buying insurance, obtaining documents, filing claims or having simple questions answered. This is something that many insurance companies have already implemented and where automated advice via chatbots, i.e. computer programs that are designed to simulate conversation with human users, can help to save time and effort. Chatbots can be deployed for more standardized customer interaction and can also be used, for instance, to provide computer-generated advice about the type of insurance coverage clients can buy. However, clients have also come to expect personalized product offers based on the history of interactions. For this, the use of more complex predictive models is necessary and this area is still in its infancy. Clearly, all of these points of contact also provide the opportunity to collect relevant information about clients to enrich the data base on which these services are provided.

Getting there is not easy for incumbent insurers since they still have to devote the bulk of their resources to maintaining existing processes and attending the existing business. Transforming a company also requires moving front and back offices in a synchronized fashion to ensure that the new approach has greater acceptance and can be implemented swiftly. The transformation process is delicate and has to also take into account the anxiety that the digital transformation provokes in a significant part of the existing workforce. Even though the forecast of Lemonade CEO Daniel Schreiber "the next insurance leaders will use bots, not brokers, and AI, not actuaries" may materialize only partially, it is clear that ultimately the digital transformation will have structural implications and that there will be winners but also losers, especially in the areas relating to distribution and customer interactions.

Another natural area of application is automated underwriting. Although insurers are used to rely on past data to assess and price risks, much of the data that would be relevant for implementing an artificial intelligence approach to underwriting is in an unstructured form and ranges from emails, to handwritten documents or sketches. Hence, before this data can be exploited, it needs to be digitized. This will typically involve scanning and the use of image processing or natural language processing capabilities. However, the challenges are far greater than the need to digitize the data. To date most practical applications of machine learning are based on supervised learning algorithms. Supervised learning relies on a training data set that can be used by a machine to learn how to predict or classify new data input. To build the training set, input data needs to be enriched by classifying it according to the desired output categories. Insurance, and especially reinsurance, is very much expertise driven, e.g. much of the claims experience has to be interpreted against changing conditions, including evolving judicial decisions. Since the classification leading to the training set has to be undertaken by experts, implementing supervised machine learning methodology is costly and time consuming. A potential way of dealing with this obstacle could be to combine machine-learning methods with a more traditional expert system-approach from the early days of artificial intelligence. Another promising direction would be to capture expert knowledge during regular business activity. At any rate, more fundamental research seems required to explore the possibilities of weakly supervised and unsupervised methodology.

As already mentioned the digital transformation encompasses more than the application of data science. It also includes the possibility of redesigning key processes to make them more efficient by the application of digital technology. One such technology is block chain, which amounts to being a shared, public ledger with a counterparty validation procedure that is not subject to central control. Key processes to which this technology has been applied are online payments and most prominently crypto currencies such as bitcoin. A crucial advantage is the elimination of third-party vendors who ensure that counterparties to a transaction are verified. This can lead to lower costs and potentially propel forward the development of micropayment systems. More generally, block chain can be envisaged as being used in any settlement process and as the platform for smart contracts, i.e. contracts that automatically trigger certain actions subject to predefined conditions. Although it is clear that block-chain technology has the potential to improve the efficiency of and enhance the trust in certain processes, the impact of block-chain technology may not be as disruptive in insurance as other digital technologies (Naylor 2017).

One area in which block-chain technology has been implemented is Insurance Linked Securities (ILS), which are investment instruments that enable the transfer of insurance risk to financial markets. For instance, Solidum Partners, a Zurich based investment management firm who specializes in ILS was the first to issue an ILS securitization on a private block chain in 2017 (Sandor 2018). Block chain has proved to be a cost effective platform for settlement in the ILS space. Less clear is whether smart contracts are viable for the greater part of reinsurance type risk transfers. This is because, for instance, reinsurance is still mostly indemnity based and relies on complex contracts that require loss adjustment to take place before settlement. As a result, at least for the moment, large scale automatic settlement does not seem to be within reach. However, progress has been made, e.g. by the B3i Blockchain Insurance Industry Initiative, founded by a large consortium of insurance firms to explore the potential of using Distributed Ledger Technologies within the re/insurance industry for the benefit of all stakeholders in the value chain (https://b3i.tech/home.html). In other, more standardized areas, smart contracts might be easier to conceive. However, also there, some obstacles exist. There are, of course, liability issues, e.g. with respect to technological failure, or the rigidity which results in less flexibility to correct errors once the contract has been closed. Limitations notwithstanding, the insurance sector should not lose sight of smart contracts even though their potential may take a while to realize.

Overall, the digital transformation is likely to result in structural changes in the industry with parts of the value chain being attacked by newcomers. Who ends up servicing which part of the value chain, remains to be seen. One area where incumbents have a clear advantage is as risk carriers. Indeed, startups are typically reluctant to bring risks on their balance sheet because of the large amounts of regulatory capital that is required. Moreover, incumbents have a long experience in underwriting which is not easy to build up (McKinsey, 2018). However, as the value chain is disassembled, profit margins will tend to decrease and cross-subsidies across the value chain will become more difficult to achieve. As a result, an efficient risk and capital management will be a critical competitive advantage for incumbent insurers and they would be well advised to pay increased attention to improve their risk and capital management capabilities. This includes a better understanding of the drivers of value of a risk carrier.

4. Data availability, Protection, and Regulation

An important question is how an increase in data availability will influence the insurance business model and to what extent data protection based on regulatory requirements is necessary.

Data availability can be increased by introducing new product forms providing an extensive digital monitoring, e.g., via apps and wearables. A current research paper by Brown et al. (2018) uses a classical agency model setting and introduces high risk and low risk policy-holders. Thereby, the policyholders in focus cannot assess their own risk type. In addition, some policyholders possess an inherent aversion against sharing private information. This subgroup of policyholder consists – like the ones who are willing to share private information – out of low and high-risk types. In an insurance equilibrium allowing for cross-subsidizations, utility is shifted from individuals who do not reveal their private information to those who do. Such an effect can be interpreted as a form of discrimination. Possible solutions include a regulation of the use of data for risk classification and pricing or measures to improve data security in order to reduce policyholders' privacy concerns.

Several new insurance models using intensive digital monitoring had been started in many insurance markets. Examples are GPS based motor insurance (e.g., "insurethebox" in the UK), various forms of regular monitoring regarding life style in the health insurance sector (e.g., "Generali Vitality" or "Dacadoo") or on-demand-insurance contracts using solely a digital sales and approval process (e.g., "Lings" or "Trov"). These concepts can help to decrease effects of adverse selection and moral hazard. In particular, a reduction of agency costs is possible via self-selection by the policyholders. Moreover, the technology allows for real-time hints and incentives for loss-prevention. With the help of new forms of digital monitoring, transaction costs and particular forms of ex-post moral hazard (for instance insurance fraud) can be avoided. However, there are also a couple of major shortcomings approaching with new forms of digital monitoring in the insurance sector. Insurance companies must reflect critically if they want to execute educational measures on their customers. Data security and data privacy is a major concern in this kind of setup. Transferring data to the insurer can perform disadvantages to policyholders in other insurance segments and areas outside the insurance market. In addition, press feedbacks on new concepts of digital monitoring are rather negative (with reputational effects on the insurance business): Typically, it is assumed that insurance companies aim only to focus on profitable and low-risk customer groups and do not want to offer supply for others. In order to tackle these aspects and to avoid general reputation risks, the insurance industry could stick to a self-regulatory framework and clearly define, which data is used for which proposes and limit their risk classification and pricing factors to certain criteria only. This would mean that particular information (e.g., life style or genetic information) could not be collected or used by providers of insurance products.

Data protection is in particular in the health sector a central issue. Until today, there have been several cases of medical data breaches, cyber virus assaults, and re-identification attacks against genomic databases. In particular, genomic data pose special privacy problems (Naveed et al. 2015): This kind of data is inherently identifying, cannot be changed (as passwords can), have unique statistical regularities, contain sensitive and personal information to individuals and their relatives, and their leakage can expose individuals to genetic discrimination. In order to tackle these issues for Switzerland, a cooperation of five research groups across the ETH domain including the Swiss Data Science Center has been formed to a “Data Protection for Personalized Health DPPH” lab (cf. https://dpph.ch). The three main goals of the research lab are a) to address the main privacy, security, scalability, and ethical tasks of data for allowing effective “P4 medicine”, b) to define an ideal balance between usability, scalability, and data protection, and c) to install a suitable set of computing tools.

Data privacy and security is also a major concern to policyholders – private consumers as well as companies. Using the classical risk management cycle (with risk identification, risk assessment, risk response, and risk monitoring), checklists regarding different events are a solid concept to measure a potential risk exposure. In a first step, this form of standardization allows a comparison of the underlying risk of different policyholders and the use of KPIs. In a second step, risk indicators can be used to generate various risk scenarios. Finally, the contribution of each key indicator to potential outcomes is simulated. Based on a traffic light approach (green, amber, red), tolerance levels are defined and several actions with timelines are built on the findings.

The availability of more data will certainly affect major parts of the insurance business model – like pricing and risk classification. If additional data and new forms of digital monitoring (for instance via apps, wearables or GPS technology) provides better information regarding the individual’s true loss distribution, a larger price range should result in a competitive market environment. As long as no severe effects on the demand side occur, diversification benefits within the insurer’s portfolio remain mostly unchanged. Nevertheless, if high-risk and low-risk individuals can be identified in the future with much higher accuracy, it may happen that certain groups within the society cannot afford insurance coverage any more. Such a development could result in regulatory interventions and limit the insurer’s freedom of risk classification. However, such regulatory actions can increase problems of adverse selection and moral hazard.

The insurance business model is based on stochastic claims and the possibility to diversify unsystematic risk. For risk-averse policyholders who cannot replicate future cash-flows, the participation in an insurance pool is beneficial (cf. Albrecht and Huggenberger 2018; Gatzert and Schmeiser 2013). The merits of pooling claims however is rather minor if the individual’s loss volatility is small. For instance, if specific information like DNA, life style factors etc. allow a very good estimation of the life expectancy with only tiny derivations, the willingness to pay for insurance is heavily reduced for rational and informed policyholders. In an extreme case, in which things become deterministic on an individual’s level via the possibility of a precise predictability, insurance becomes obsolete giving equally informed market participants.

Clearly, such an extreme scenario for general insurance business lines is rather unrealistic. Therefore, we must assume that better-informed insurance providers use “cherry picking” techniques. Data driven companies could have general advantages compared to traditional insurance companies for various reasons. Firstly, they are more familiar with digital monitoring techniques. Secondly, customers are rather willing to share data with technology companies compared to traditional insurers. Thirdly, customers typically have more touching points with technology driven companies and hence, these providers may have better information about customers’ preferences and needs. Traditional insurers could lose the direct contract to their customers and rather stay as risk carriers in the market. Alternatively, they could go in the direction of technology driven companies or try to participate on the data obtained by those providers. However, we must assume that technology driven companies would not give data to insurance companies free of charge. In addition, it seems important to provide fair market conditions: Large digital providers like Google seem not to fulfil local rules with respect to the protection of data privacy or taxes. Such a procedure – if staying unmolested – puts great disadvantages on insurance companies that have to consider the local regulatory framework.

About the Swiss Risk and Insurance Forum. The Swiss Risk and Insurance Forum was created in 2014 with the mission to bring together experts from academia, the insurance industry, regulatory bodies and consulting companies to discuss (typically technical) topics that are relevant to the insurance industry. The main objective is to provide a platform on which people from academia can interact with those involved on the more practical side of the insurance industry. This shall facilitate the knowledge transfer in both directions helping enrich the research agendas of the academic institutions and enabling those dealing with practical matters to partake in the newest academic developments. The 2018 workshop on Insurance: Models, Digitalization, and Data Science gathered 29 experts for one and a half days of presentations and discussions.

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