Ratemaking for Emerging Liabilities in Property & Casualty Insurance: Practical Tools and Enriching Imagination

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Abstract
The main idea for this paper is to understand various emerging landscapes for ratemaking. It is pointed out that the traditional actuarial approach of waiting until products are developed and launched and there is sufficient and credible data and only then to proceed with ratemaking is inadequate and severely limited for the challenges of today. Unfortunately, the approach required to handle emerging landscapes of new risks, products and liabilities does not require few new algorithms but a complete overhaul of our mentalities and technical competencies. No more can we effectively isolate ratemaking from other actuarial undertakings as holistic trends are tearing down silos swiftly. First section of this report highlights key new quantitative tools that are compulsory for emerging liabilities ratemaking. Second section of this report details the more important aspect of training ourselves qualitatively and building a new mentality for handling the new challenges of ratemaking for emerging liabilities. The conclusion we arrive at is that cross-disciplinary training is rapidly becoming necessary in our fast paced environment. Emerging risk research is still a relatively nascent field when compared with actuarial science, and generally lacks a well-established methodology. This paper aims to fill this gap.

Keywords: Big Data, Deep Learning, Topology, Complexity Science, Emerging liability ratemaking, Sociology of Finance.

1. INTRODUCTION

This traditional reactive approach to actuarial ratemaking has a number of limitations including that time is of the essence for new and emerging products and emerging risks/liabilities/products like drone insurance, driverless cars insurance, telematics, cyber insurance, impact of genetic engineering and antibiotic resistance, personalized medicine, 3D printing, growing epidemics, impact of cryptocurrencies, impact of new generation 'millenials' and disruptive 'fintech', impact of rapidly changing weather, impact of crowd sourcing and collective wisdom like prediction markets and others. Changing market conditions are also there; permanent lower prices of oil, increase in alternative investments like impact investing, rise in Islamic finance like Islamic insurance or 'takaful' and so on. If we keep waiting until credible data emerges, we actuaries will forever remain behind and less influential than other intellectual bodies/professionals as changes are very rapidly oscillating and it seems that there will always be new emerging products and landscapes. New risks, products and liabilities are emerging and are becoming antiquated before they can even ossify. Constant revolutionizing of technology constantly keeps our social relations in everlasting uncertainty. Preemptive action and pro-active in the nick-of-time involvement is now perhaps the only way for actuaries to go about dealing with the rapid fast moving present and future.

It is important to clarify the rapid changes instead of becoming mystified by them. We are currently living at the intersection of Risk Society and Knowledge Society. Knowledge Society [1] is where Knowledge has now superseded both capital and labor as the factor of productions employed by the society. Like investing capital leads to greater capital, knowledge production is becoming self-sufficient too. It is a utility, a public good, a private good and ultimately a commodity now in today's society but the distinct feature is that it is changing the nature of 'commodities' itself.

As for Risk Society, Ulrich Beck defines Risk Society [2] as:

> *"a systematic way of dealing with hazards and insecurities induced and introduced by modernisation itself." (Beck, U. 1992)*

Financial contagions such as the financial crisis of 2008, EU crisis over Greece sovereign debt, impact of shale oil in recent years especially 2014 to present over oil producing economies particularly Russia as well as environmental crisis likes global warming, Chernobyl melting of nuclear reactor etc are living and breathing proof of the risk society. Cyber hacking and terrorism from armed radical groups are also part of the manufactured risks of the risk society.

It is not just man-made events but natural disasters too are ever on the increase worldwide. Munich Re study [3] shows that over the past few decades, loss events related to weather increased by 5 times in North America, by 4 times in Asia, 2.5 times in Africa and 2 times in Europe respectively. Munich Re data also shows that large proportion of these losses occurs due to climate change.

Living at the intersection of knowledge and risk society presents the paradox where we have more opportunities to apply and gain from knowledge and skills but that we are simultaneously more vulnerable and fragile to increasing crises and compounding of manufactured risks which risks us losing our civilization. However, this is not surprising for complexity science which formulates a powerful idea for such experiences. We live at 'the edge of the chaos' where we are both strong and fragile at the same time [4].

In such situation, it is imperative for the modern actuary to:

1. Improve our tools. We live in every increasing complex system and solve complex problems but many of our tools are too reductionist for handling these nuances.
2. More importantly, change our mentality; qualifying as an actuary alone will not guarantee everything. Many tools will likely be outdated once an aspiring actuary ultimately becomes a fellow. Familiarity bias where we continue using tools which we know rather than what is the best coupled with being ambiguity-averse can prove to be our Achilles' heel. We need to learn more diverse subject areas and viewpoints, strengthen qualitative understanding, and be more pro-active and better at communication. Continuous learning has to be in our bones.

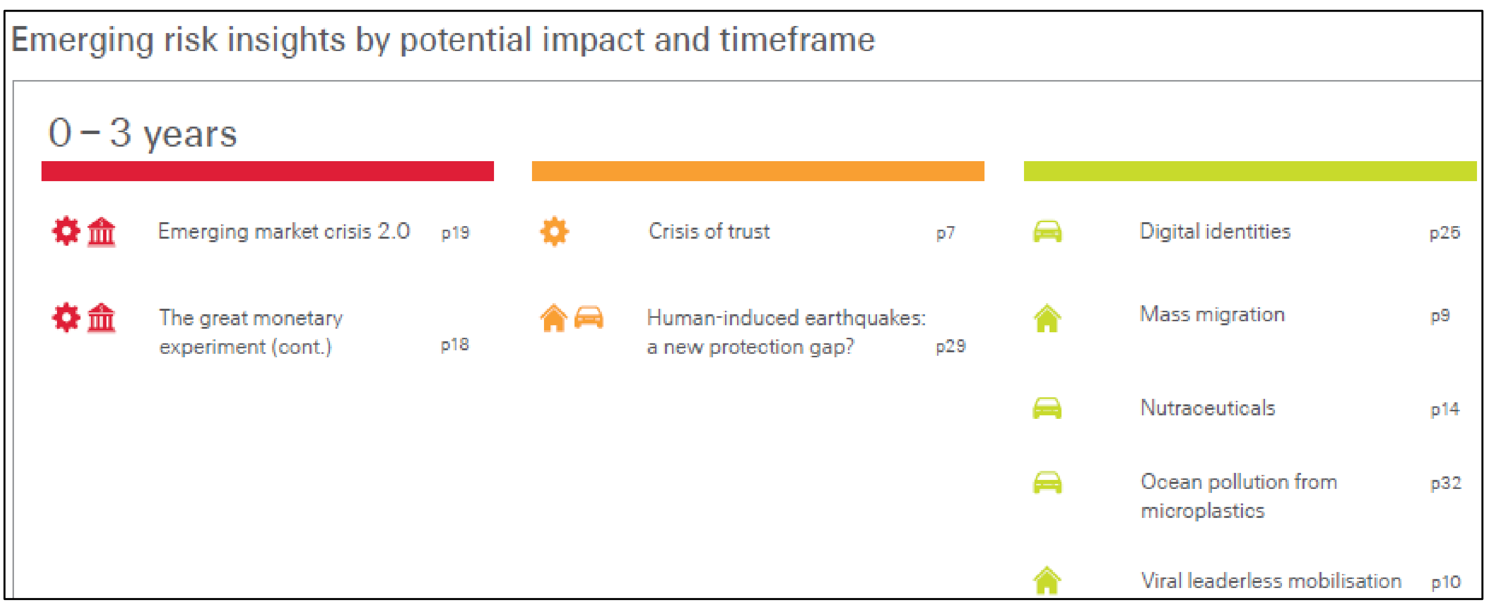
The scope of this report shown above is ambitious given the restrictive word limits. Hence, the purpose of this report will be to point to a framework, an area under development and try to point the way which the reader will have to walk herself. This report does not intend to give detailed explanation of each model it mentions. Rather, it will endeavor to provide intuition coverage of key ideas in the models that it covers in helping to shed more light on scope mentioned. It is advised and encouraged that those models and measures described here that are not known to the reader be explored further by reading the references given in this report. These references can serve as useful resources to enable and advance current practices as well.

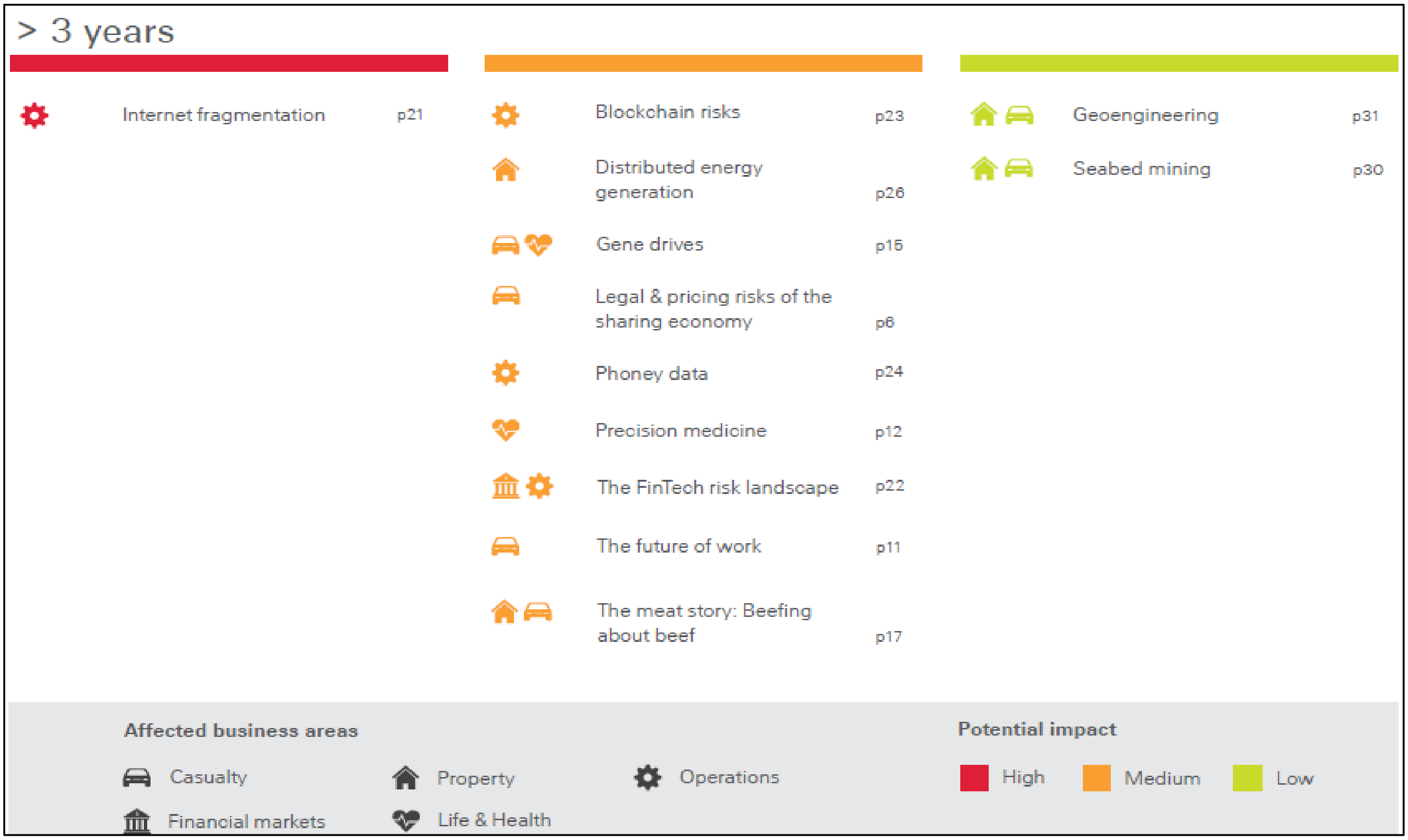
It is emphasized that emerging risks do not suddenly appear from nowhere and that there are always possible leading indicators, even though they may be rare and difficult to comprehend. Emerging risks are the contextual product of an evolutionary process these take time to develop and reveal themselves [5].

A vital composition of emerging risk is the combination and integration of existing risks. The combined symptom can be assumed as an emerging risk but actually it is deeply rooted in existing risks as well; it is the potent and dynamic configuration and integration of existing risks that often give rise to new risks [6].

This is a worthwhile exercise only if qualified by the caution that any general statement can almost instantly yield an exception to it as both bodies of inquiry (quantitative modeling and qualitative profiling) are much more complex than any brief assessment would suggest.

Emerging risks by Swiss Re have been categorized by potential impact and timeframe as follows [7]:





This info-graph presents 21 key emerging risks as researcher by Swiss Re. For further details, refer to Swiss Re SONAR New Emerging Risks Insights, May 2016.

In a nutshell, the contents of this report can be encapsulated as follows:

1. Key Quantitative modeling tools
    - i. Overview
    - ii. Complexity Science
        - i. Network Theory
        - ii. Agent Based Modeling
    - iii. Topology
    - iv. Deep Learning
    - v. Machine Learning
        - i. Exploring our data
        - ii. Predictive Modeling
        - iii. Unstructured data mining and text analytics
    - vi. Big Data
        - i. Key tools for transformation
        - ii. Big data application case study

2. KEY QUANTITATIVE MODELING TOOLS

2.1. Overview

Ratemaking is an exercise in complex systems. There is a myriad of complex features in action simultaneously and despite our best predictive modeling, it can have low predictive power beyond a reasonably short period of time. But while predicting the macro- structures upon which to base ratemaking upon can be less effective, we can train our approach, our tools and our management of ratemaking to be better evolvers rather than better predictors alone [8].

There is a traditional trade-off between what is known as homogeneity and credibility, where the actuary must decide how finely to divide up the databases available. One reason that there is an almost infinite variety of actuarial models is that each model necessarily incorporates an element of judgment or intuition or speculation in the definition and weighting of probable future events [9].

But while macro situations are indeed hard to forecast, we can see how they arise and emerge out of 'rules' and cognitive maps that we follow as micro agents from the starting points. These simple rules can be uncovered through game theory and behavioral finance and aptly applied onto agents for serious game simulations [10].

The List of new tools and paradigms covered in this section and the appendix A are:

1. Complexity Science
2. Game Theory
3. Gamification
4. Fuzzy Logic
5. Topology
6. Deep Learning
7. Machine Learning
8. Big Data

2.2. Complexity science

Key insights of complexity science which has delivered better results than traditional approaches are [11]:

- Complex systems with all their splendid intricacies actually arise from adaptive iterations (actions-reactions) of agents following simple behavior rules.
- Predicting the long-term behavior of complex systems is highly improbable as they are too rapidly changing and complex to predict other than over a reasonable short term.
- Agents can start out in complete chaos, and by merely following simple behavior rules generate a complex system that is highly structured without any external central control mechanism like the Government or Regulator.
- Complex system properties often follow power laws characterized statistically by Pareto-Levy distributions. This shows snowballing effects where a single small tendency over time becomes exceptionally large; i. e, the rich get richer, the poor get poorer.
- Harmony and equilibrium are more fantasies than reality. Common realistic pattern of emergence is punctuated equilibrium which exhibits long periods of relative stasis, interspersed with brief periods of explosive productivity; stagnancy followed by paradigm shifts and 'new normals' and so on.
- Complex systems are at the same time robust and fragile. For example, many real-world networks such as the Internet are robust to random attack, but fragile to focused attack.

There are at least forty measures of a complex system's complexity. These measures relate to how hard it is to describe the system, how hard the system is to create, or the degree of its structure. Examples of measures are Transaction information, Network complexity, Degree of hierarchy, Algorithmic information content, Logical depth and Statistical complexity.

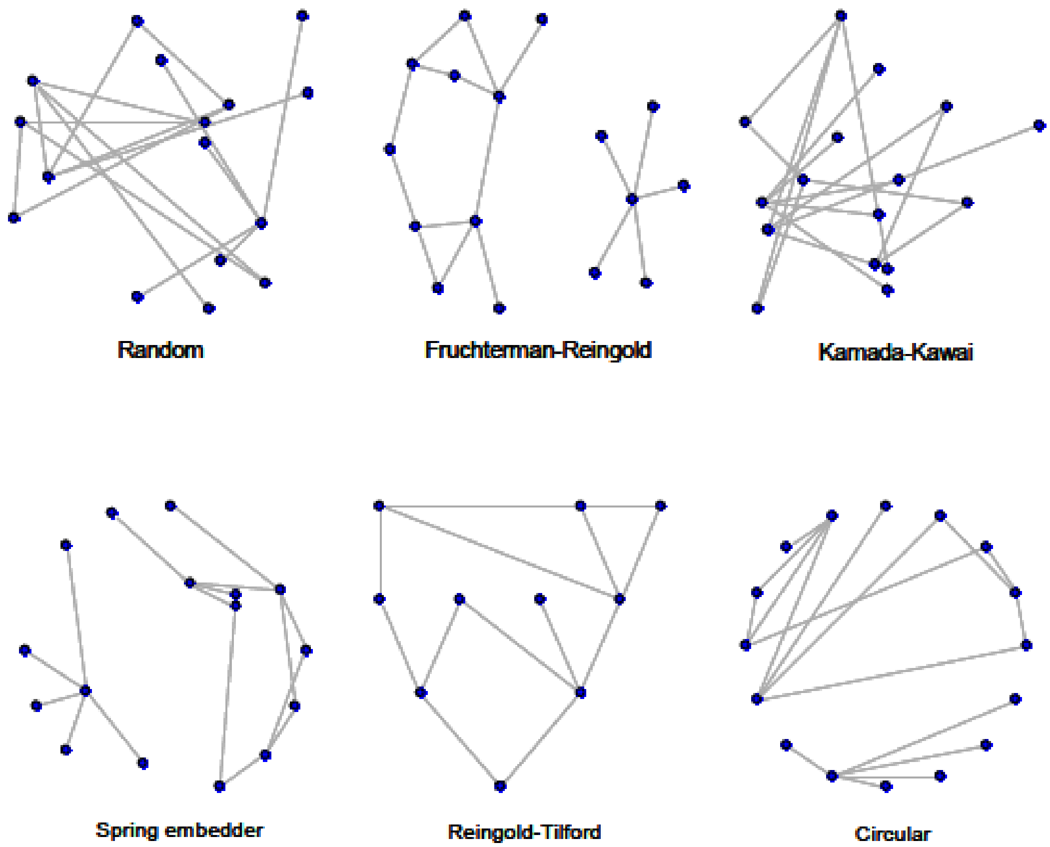
2.2.1. Network theory [12]

Complexity science shows us that we handle complex systems like the economy, health care administration, financial stock markets etc. on a daily basis. New risks from these systems do not arise out of the blue but that the a portion of the clusters and syndrome characterizing the complex system morphs to another syndrome with most of the components remaining fundamentally similar even though their manifestations might have changed.

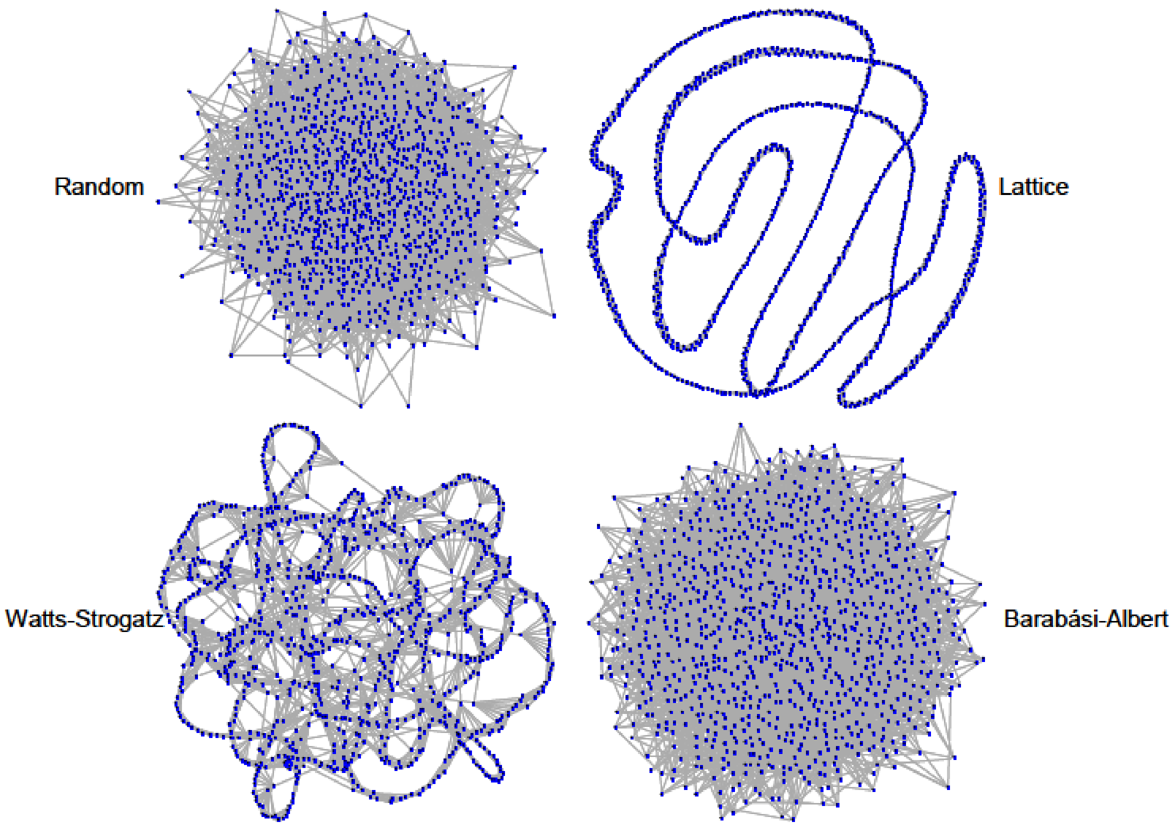
To analyze these clusters, changes in syndromes and consequently the core that remains fundamentally the same, complexity science applies network theory and analysis to explore the underlying structure.

Network theory studies agents and the relationships between them. A network study from several years ago demonstrated that the seemingly tiny influence that trading has on the market becomes increasingly significant as the number and complexity of financial instruments increases. The generic result is violent market fluctuations and instability. Financial institutions still find ways to profit by creating and selling new derivatives, even if these deliver no benefits to the market and actually drive the system toward trouble.

Graphs are first established in **"layouts"** which show correlations between agents and their inter-relationships using graphs. A number of archetypical layouts for graphs are shown as follows:



In addition, there are four main models in network theory: 'random', 'lattice', 'Watts-Strogatz' and 'Barabasi- Albert'. Each of these models with 1,000 vertices each has been shown by Alan Mills using the Fruchtermann- Reingold layout:



In his speech, Andrew Haldane applies network theory and observes that over the past 20 years the world financial network has become:

- denser (more vertices)
- more complex (more edges)
- more asymmetrical (more skewed degree distribution)
- a less separated "small world" (lower mean geodesic)

This shows that networks emerge rather than being created and can be used to analyze emerging risks and liabilities effectively. For instance, targeted attacks against venture capitalists to drone technology will mean that this technology might never actually take-off whereas random attacks on viability of drones is not likely to affect its development. Collapse in one area of the economy can translate into economy wide contagion and confidence shaking emerging risks like antibiotic resistance, ebola and other epidemics will contagion on health insurance through loss of confidence far greater than anticipated through traditional actuarial and economic theory.

2.2.2. Agent based modeling [13]

There is a key deficit of network theory. It is that it relies on historical data to generate networks; we can see networks that have evolved and analyze them for 2008 financial crises and current products like telematics but what about networks that are yet to emerge?

Agent based modeling effectively addresses this shortcoming. It is recognized that network theory uncovers a lot of important underlying structures that blind traditional actuarial theory. Moreover, key concepts like robustness, fragility, emergence, the topological geodesic structure into particular network models etc. are likely to remain the same even though their manifestations will be different for emerging risks.

Hence, to organize behavior rules to set as base for agent based simulations, Common tools that complexity scientists use are extrapolating network trends from similar risks like extrapolating telematics network for drone insurance, game theory, genetic algorithms, heuristics and cognitive tendencies that we humans apply uncovered by behavioral finance, and neural networks. See Appendix A1for Game Theory applications to ratemaking in detail.

Agent based modeling combined individual decision and network rules to model policyholder behavior, allowing us to simulate behavior at an individual level and then analyze the overall, aggregate outcomes. These models simulate the simultaneous operations and interactions of multiple individuals to recreate a system and predict complex phenomena. This process results in emergent behavior at the macro level based on micro-level system interactions.

Real life indices can be modified and then applied to the serious game simulations. For instance, the Chicago Board Options Exchange Volatility Index, (CBOE VIX) is a well-established indicator of market risk aversion tendency, or risk appetite. The value on the VIX is basically the square-root of the risk neutral expectation of S&P variance over the next 30 calendar days. This can indicate the 'fears' and 'ambitions' of the market cycle appropriately.

Other methods

Gamification is applying games to non-gaming situations and can be simulated through agent based modeling as well as run by real humans like on mobile apps. Traditionally, Gamification can help insurance business teams give the right discounts and pricing for large and fast deal closure. Customer responses and playing behavior can also show what emerging risks they are anticipating and what matters most to them. It can also be used to train sales teams on the product by using scenario based technique and objective methods of questioning to more quickly and pro-actively assess emerging liabilities. This could help decrease the time taken to build competency to be effective sales person by 10% to 30%. See appendix A2-Gamification for detailed advantage of using gamification for emerging risks [14].

We have credibility problem when doing ratemaking for emerging products. Reality is also less precise and more fuzzy than we comprehend. Aside from other methods mentioned in thiis report, Fuzzy logic can also bring useful solutions to us on the table. See appendix A3-Fuzzy Logic for detailed explanation on fuzzy logic as well as their applications on emerging liabilties[15].

2.3. Topology

Topology is the mathematical study of the properties that are preserved through deformations, twistings, and stretchings of objects. Tearing, however, is not allowed [16]. Topology can be used to abstract the inherent connectivity of objects while ignoring their detailed form. Put simply, Topology is a mathematical discipline that studies shape and assumes that shape has meaning [17].

A sizeable portion of financial and actuarial research is built upon classical applications of Linear Algebra (such as regression analysis) and Stochastic Calculus (such as valuation models). As a result, these methods focus on *geometric locations* rather than *logical relations*. Traditional actuarial models could be complemented with Topological and Graph-Theoretical tools that recognize the hierarchy and relationships between agents in the system. While Black-Scholes and quantitative finance looks challenging mathematically, the mathematics behind it is quite old and we must keep up with recent mathematical discoveries like topology especially because they are revolutionizing every aspect of science [18].

The problem with Linear Algebra and Stochastic Calculus is that these were not designed to study complex adaptable systems. Linear Algebra focuses on locations in Euclidian geometry, thus the "linear" term. Stochastic Calculus shares that focus, by concentrating on the measurement of changes of geometric location associated with a random variable, the speed of that change, etc. While Linear Algebra can answer questions such as how closely together a system moves, it cannot recognize what is a system's shortest path of propagation, what nodes can shut down a network, or what connections are most critical to ensure network flow [19].

A Topological study of the financial system provides a relationships map to how markets are arranged and interconnected. A Graph Theory study of the financial system tells us about the role that various nodes play. This is useful to market participants, because it explains how information propagates through the system, allowing them to monitor capital flows and anticipate price trends [20].

Anticipating price trends and modeling of demand is a key requirement to insurance ratemaking and can be used to simulate price trends and cycles for emerging liabilities. One appropriate topological application for this purpose is Stochastic Flow Diagrams (SFDs). Stochastic Flow Diagrams (SFDs) is a novel mathematical methodology that can help us visualize the complex network of demand and supply flows scattered around punctuated equilibrium. We propose SFDs that combines elements of Graph Theory and inferential statistics to visualize the structure of a complex system, allowing for an intuitive interpretation of its state and future course. The SFD method takes into consideration the dynamic properties of the system, determining the direction of the flows in terms of lead-lag and causality effects. SFD connectivity is determined by statistical significance of the graph's arcs, which are weighted based on the flow carried through the arcs involved. Because SFD maps a dynamic system, it incorporates a time dimensionality, where crossing each arc represents a unit of time elapsed [21].

Aside from SFDs, there is also Topological Data Analysis. Topological Data Analysis (TDA) refers to the adaptation of this discipline to analyzing highly complex data. It draws on the philosophy that all data has an underlying shape and that shape has meaning [22].

The machine intelligence approach advocated by Ayasdi (a startup founded by Stanford professors) combines topology with machine learning to achieve data-driven insights instead of hypothesis driven insights. Machine learning on its own have significant limitations. Clustering, for example, requires an arbitrary choice of clusters which the analyst has to specify. With dimensionality reduction techniques, the danger is on missing the subtle insights included in the data that can potentially prove to be very useful to the analysis. Including topology with machine learning overcomes these drawbacks effectively [23].

The topology visualizations capture the subtle insights in the data while also representing the global behavior of the data. From the nodes identified by the topology network diagrams from the data, clusters are identified and each cluster is fit onto a model that fits it more properly so that instead of a one-size-fit-all model, different models are applied to different regions of data for maximum predictive potency [24].

On another note, by following the lead by the author Ovidiu Racorean [25] and generalizing his topological approach from stock markets to ratemaking, a surprising image of premiums can potentially arise if the price time series of all *lines of business* are represented in one chart at once. The chart can evolve into a braid representation of the general insurance portfolio by taking into account only the crossing of stocks and fixing a convention defining overcrossings and undercrossings. The braid of stocks prices has a remarkable connection with the topological quantum computer. Using pairs of quasi-particles, called non-abelian anyons, having their trajectories braided in time, topological quantum computer can effectively simulate the premium levels and behavior encoded in the braiding of the portfolio. In a typically topological quantum computation process the trajectories of non-abelian anyons are manipulated according to the braiding of stocks and the outcome reflects the probability of the future state of stock market. The probability depends only on the Jones polynomial of the knot formed by plat closing the quantum computation. The Jones polynomial of the knotted stock market acts, making a parallel with the common financial literature, in a topological quantum computation as a counterpart of a classical technical indicator in premiums arrived by let's say a Generalized Linear Model. The type of knot stock market formed is also an indicator of its future tendencies.

Following this approach, premium pricing signals can become a process of writing a quantum code and the topological quantum computer is the perfect device designed to read it for decoding the premium pricing market behavior. The end of typical topological quantum computation consists in fusing the pairs of non-abelian anyons together, a process that results in plat closure of the braided trajectories of anyons. The outcome of the topological quantum calculation is referring at the final state of the system and expresses the probability of the insurance market to end in a certain state, say soft or hard underwriting cycles [26].

2.4. Deep Learning

Up till recent past, the artificial intelligence portion of data science was looked upon cautiously due to its history of booms and flops [27]. In the latest stream of events, major improvements have taken place in this field and now deep learning, the new leading front for Artificial Intelligence, presents promising prospect for overcoming problems of big data. Deep learning is a method of machine learning that undertakes calculations in a layered fashion starting from high level abstractions (vision, language and other Artificial Intelligence related tasks) to more and more specific features [28]. Deep learning algorithms essentially attempt to model high-level abstractions of the data using architectures composed of multiple non-linear transformations. The machine is able to progressively learn as it digest more and more data and its ability to transform abstract concepts into concrete realities has opened up a diverse plethora of areas where it can be utilized. Deep learning has various architectures such as deep neural networks, deep belief networks, Deep Boltzmann machines and so on that are able to handle and decode complex structures that have multiple non-linear features [29].

Deep learning offers us considerable insight into the relatively unknown unstructured data which is 80% of the data that we generate as per IBM [30]. While traditional data analysis before 2005 focused on just the tip of the iceberg, the big data revolution sprang up and now deep learning offers us a better glimpse into the unconscious segment of data that we know exists, but is constrained in realizing its true potential. Deep learning helps us in both exploring the data and identifying connections in descriptive analytics for ratemaking but these connections also help us in price forecasting what the result will likely be, given the particular combination as the machine learns from the data.

Deep learning has inputs, hidden layers where they are transformed by the weights/biases and output which is achieved through choice of activation function from various functions available (Softmax, sigmoid, hyperbolic tangent, rectified linear, maxout and so on). The weights/biases are learned by feeding training data to the particular deep learning architecture. Deep learning is different from neural networks as it has multiple hidden layers whereas neural network only has one [31].

A de-mystified the foundation of deep learning is mostly a way of using backpropagation with gradient descent and a larger number of hidden neural network layers which is certainly not new. However, revival of deep learning was possible after 2010 and onwards due to drastically more computational power from GPUs, bigger datasets, and some key algorithm tweaks mainly dropout and AdaGrad to increase accuracy rates. Moreover, the unique feature of deep learning is that it allows individual parts of the model to be trained independently of the other parts [32].

Deep learning models can recognize human faces with over 97% accuracy, as well as recognize arbitrary images and even moving videos. Deep learning systems now can process real-time video, interpret them, and provide a natural language description. It is becoming increasingly established that deep learning can perform exceptionally well on problems involving perceptual data like speech recognition image classification and text analytics [33].

In a single formula, this is the formula for neural networks (for hyperbolic tangent activation function) [34]

Put all together in a single equation, we obtain:

$$p(x) \quad = \quad \beta_0 + \sum_{i=1}^{n_h} \beta_i \ \tanh\left(\alpha_{i,0} + \sum_{j=1}^{n} \alpha_{i,j} x_j\right).$$

So that essentially, p(x) = linear+ non- linear.

Aside from exposures, the other side of ratemaking is losses and loss trends. By building deep learning models we can analyze images to estimate repair costs. Also deep learning techniques can be applied to automatically categorize the severity of damage to vehicles involved in accidents. This will more quickly update with us more accurate severity data for modeling pure premiums [35].

Deep learning is becoming the method of choice for its exceptional accuracy and capturing capacity for unstructured data. This is also emphasized ahead in section machine learning-unstructured data mining and text analytics [36].

One issue however with deep learning is trying to find the hyper-parameters that are optimum. The possible space for consideration is very large and it is difficult and computationally intensive to understand each hyper parameter in depth. One potential solution which the author of this report identifies is the possible use of genetic algorithm to find optimal hyper parameters. Genetic algorithms are already used on GLMs on R 'glmulti' package to select optimum GLM equation as per a given criteria usually Akaike Information Criterion or Bayesian Information Criterion.

Moreover, another algorithm has been used to optimize both structure and weights of a neural network. ES HyperNEAT is Evolving Substrate Hyperbolic Neuroevolution Of Augmenting Topologies developed by Ken Stanley. It uses a genetic algorithm to optimize both the structure and weights of a neural network. Following from this, maybe ES HyperNEAT framework can be extended to deep learning so that genetic al genetic algorithm can optimize both the structure and weights of the neural networks in deep learning as well [37].

Another problem is over fitting. Machine unlearning can be used to solve this. Explain machine unlearning in one sentence. Machine unlearning puts a new layer of small number of summations between the training data and the learning algorithm so that the dependency between these two is eliminate. Now the learning algorithms depend only on the summations instead of the individual data from which over-fitting can arise more easily. No retraining of remodeling is required [38].

There are huge numbers of variants of deep architectures as it's a fast developing field and so it helps to mention other leading algorithms. The list is intended to be comprehensive but not exhaustive since so many algorithms are being developed [39] [40].

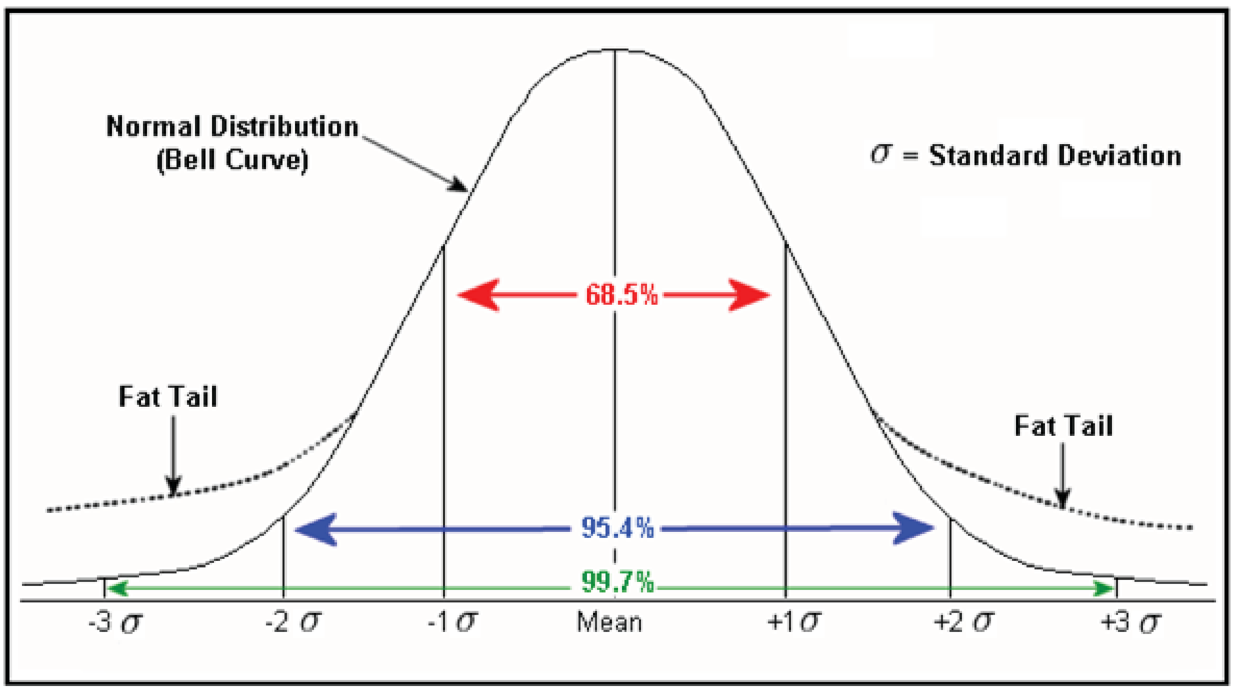
1) Deep High-order Neural Network with Structured Output (HNNSO).
2) Deep convex network.
3) Spectral networks
4) noBackTrack algorithm to solve the online training of RNN (recurrent neural networks) problem
5) Neural reasoner
6) Reccurrent Neural Networks
7) Long short term memory
8) Hidden Markov Models
9) Deep belief network
10) Convolutional deep networks
11) LAMSTAR are increasingly being used in medical and financial applications. LAMSTAR is Large memory storage and retrieval neural networks.
12) Deep Q-network agent. Google DeepMIND uses this and it is based on reinforcement learning which is a major branch of psychology, aside from evolution.

2.5. Machine Learning

'In pricing, are we swapping specific risk for systematic risk?' [41]

The hypothesis is that in normal market conditions, premiums are kept at low levels to increase revenues and market share. The traditional approach requires precise figures (point estimates) and so leads to understatement of uncertainty. This keeps a comfort level for us but the hidden risk of underpricing in our premium estimates is hardly given the attention it merits. This crops up from the rug it was shrugged under in stressed market conditions when high loss ratios then systematically proven to be unsustainable.

In other words, are we causing the fat tail problem [42] by our practices? Even if not, what can be done to reduce the fatness of such tails and bring the hidden uncertainties onto the surface explicitly? [43]

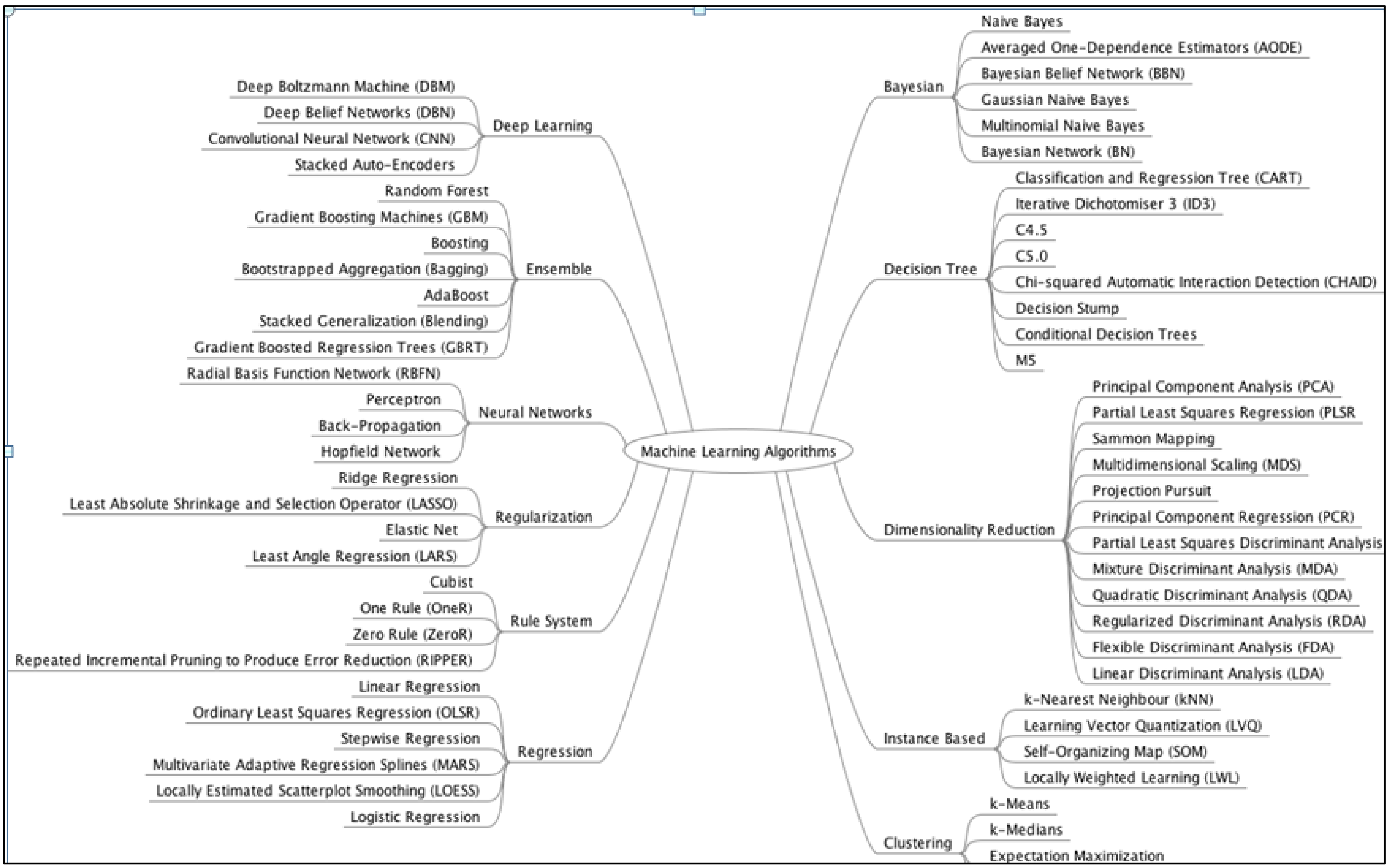


A fat tail exhibits large skew and kurtosis and so there is a higher probability for large losses compared to other distributions like normal distributions. This higher loss tendency remains hidden under normal market conditions only to resurface in times of higher volatility. Complexity scientists call fat tails the signature of unrecognized correlation. Fat tails are an indicator that cascading risks are influencing the probability distribution.

While this discussion does not provide an exhaustive guide to the machine learning tools and algorithms available to the actuary, it provides an outline of them while supplying a context for them in the ratemaking process.

We argue that what was perceived as uncertain can now be made less uncertain with machine learning. Also the uncertainty should be captured from where it was partly generated like risky classes were underwritten which later lead to greater pricing uncertainty and so on.

Machine learning has brought about an explosion of algorithms in recent times. As actuaries are not traditionally trained for machine learning, and because there are so many algorithms, it can lead to 'paralysis through analysis' where one is confounded by so many choices (R's Caret package of machine learning has 147+models) and decides instead to do nothing but follow previous precedent. This mindmap, still not exhaustive, made by Jason Brownlee at Machine Learning Mastery highlights a number of diverse classes and sub classes of algorithms and approach applied in Machine Learning [44]:



Each of these models have a different bias, and hence their own strengths and weakness relative to other algorithms and areas of application. It is certainly not possible to discuss many of these algorithms so we will try to stick to 'actionable insight's produced from focusing on a small number of relevant algorithms.

With regards to pricing uncertainty and ratemaking applications in general, machine learning can be applied in ratemaking in a number of ways:

- Exploring our data
- Predictive modeling
- Unstructured data mining and text analytics

2.5.1. Exploring our data

Decision trees such as hidden decision trees or random forests can allow us to see the map and the critical paths upon which the data is proceeding. Thus, the trend and nature of even huge datasets can be understood through decision trees [45]. Decision trees are unsupervised methods of learning which means that they expose the trends within the data without relying only on what the analyst is interested in querying.

Clustering especially KNN means clustering is an imperative algorithm that exposes different clusters operating within a given data [46]. This can tell us the groupings within claim registers and premium registers like one cluster can be bodily injuries are associated with third parties that are associated with non-luxury vehicles that are commercial and so on.

Time series decomposition: There are R codes available for running this decomposition algorithm. Basically decomposition of time series takes a real-data time series and breaks it down into 1) trend (long term), 2) seasonal (medium term) and 3) random movements [47]. Such decomposition can have huge potential in understanding trends in data. For instance, claims data have trend that follow an underwriting cycle and mimics the economic cycle closely. An instance for seasonal trend can be higher sales of travel insurance in spring break and summer breaks and so on.

2.5.2. Predictive modeling

Aside from exploring the data various uncertain elements of risks can be captured for predictive modeling as well.

Generalized Linear Models (GLMs) can be applied to arrive at distribution of frequency and severity of claims. Mostly Gamma or Lognormal distributions are fitted to severity data and Poisson or Negative Binomial for frequency. Another approach is to directly apply Tweedie distribution on pure premium.

GLMM is a natural extension to GLM models as the linear predictor now contains random effects as well to incorporate fuzziness and give a stochastic feel for enhanced pricing [48].

Predictive modeling using GLMs and GLMMs can also be assigned to categorize a particular policy into its proper risk category like into predictive risk for claim likelihood for a particular policy and so on (unacceptable risk, high risk, medium risk, low risk etc). Separate modeling can then be done for each major risk category so as to expose greater insight into the ratemaking process [49]. The results from the separate models can act as a feedback loop to the risk and underwriting categories of how valid and reliable are these categories and promote greater cooperation between underwriting function and the claim/reserving function which is vital to generating adequate risk-adjusted premiums.

While it is important to select optimum risks for predictive modeling and ratemaking on a broad level, it is also vital to take the notion of 'fairness' into account. There have been couple of backlashes around ratemaking such as not using gender to quote prices, controversial social image of using credit scores to quote premiums and most recently, pricing optimization where customers and regulators have pointed out that simply market dynamics like price elasticity and consumer preferences should not lead to different premiums and that only risk factors (and not market factors) should lead to premium differentiation [50].

Complexity scientists also favor use of power law distributions for any modeling purpose like Pareto-Levy distribution. This should be tried by the actuary to apply it on severity data and compare its results with other distributions to see if any improvements have been achieved [51].

2.5.3. Unstructured data and text mining

It is well known that 80% of data is unstructured. Unstructured data is the messy stuff every quantitative analyst tries to traditionally stay away from. It can include images of accidents, text notes of loss adjusters, social media comments, claim documents and review of medical doctors etc. Unstructured data has massive potential but has never been traditionally considered as a source of insight before. Deep learning is becoming the method of choice for its exceptional accuracy and capturing capacity for unstructured data. The traditional relational databases use rows and columns in handling data but NoSQL (Not-Only-SQL) uses a number of other components such as giving unique key or hash tagging to every item in the data. Insurance companies can utilize NoSQL databases like MongoDB, Cloudera and Hadoop because it captures so many elements of reserving that were deemed belonging to the domain of uncertainty before as they were too messy and qualitative [52].

Text mining utilizes a number of algorithms to make linguistic and contextual sense of the data. The usual techniques are text parsing, tagging, flagging and natural language processing [53]. There is a correlation between unstructured data and text mining as many unstructured data is qualitative free text like loss adjusters' notes, notes in medical claims, underwriters' notes, and critical remarks by claim administration on particular claims and so on. For instance, a sudden surge in homeowners' claims in a particular area might remain a mystery but through text analytics, it can be seen that they are due to rapid growth in mold in those areas. Another useful instance is utilizing text analytics when lines have little data or are newly introduced which is our research aim here [54].

Sentiment analysis/opinion mining over expert judgment on level of uncertainty in reserves can also prove fruitful. Natural Language Processing (such as in Stanford 'CoreNLP' software available free for download [55]) is a powerful source of making sense out of the texts.

Claim professionals often have more difficulty in assessing loss values associated with claims that are commonly referred to as "creeping Cats." [56]

These losses typically involve minor soft tissue injuries, which are reserved and handled as such. Initially, these soft tissue claims are viewed as routine. Over time, however, they develop negatively. For example, return-to-work dates get pushed back, stronger pain medication is prescribed, and surgery may take place down the road. Losses initially reserved at $8,000–$10,000 then become claims costing $200,000–$300,000 or more. Since these claims may develop over an extended time period, they can be difficult to identify. Creeping cat is a big problem for emerging liabilities because mostly, we do not fully know what we are dealing with. Emerging risks like cyber-attacks, terrorism etc have shown to have huge creeping cat potential.

As discussed, predictive models can review simulated claim data from agent based modeling, network theory and other methods mentioned in this report for similarities and other factors shared by such losses, thereby alerting the claims professional to emerging risks that may have creeping Cat potential. With this information, strategies and resources can be applied at a point in time where they can be most effective in an effort to achieve the best possible outcome and control cost escalation. Additional loading on premiums can also be given on areas with higher Creeping Cat potential.

In conclusion, by measuring and exposing areas of uncertainty that are traditionally not considered, we can reduce our chances of swapping specific risk by systematic risk in our ratemaking procedures and lessen fatness of the tails and handle emerging liabilities in a more resilient manner.

Moving these data collection policies and the uses of this data from the subconscious to our consciousness is a first step in the process of potentially applying big data in a business context. The use of big data and analytics has rapidly evolved from a back-room niche to a strategic core competency [57].

Actuaries will have to understand and appreciate the growing use of big data and the potential disruptive impacts on the insurance industry. Actuaries will also need to become more proficient with the underlying technology and tools required to use big data in business processes [58]. Subsequently, this is the effort of the next section.

2.6. Big Data

2.6.1. Key tools for Transformation

The challenges of big data can be captured succinctly as follows [59] [60]:

- Volume; ever increasing volume which breaks down traditional data-holding capacity
- Variety; more and more heterogeneous data from many formats and types are bombarding the data environment
- Velocity; more and more data is time sensitive now; frequent updates are taking place instead of relying on historical old data and data in real time is being generated now by the internet of things, amongst others.
- Veracity; how valid and reliable is the data? Since now we have so much data, any point of view can be supported by selective adaption of data.

For volume, Map Reduce [61] works to harness the potential of billions of items of data. The first part is that the data is mapped down into key and value pairs; the reduce job combines the mapped data into smaller set of data by eliminating repetition and redundancy amongst others. Hadoop is open-source for handling big data, applying MapReduce and a variety of other distribution systems and clusters. and there are variants produced by many different vendors such as Cloudera, Hortonworks, MapR and Amazon. There also other products such HPCC and cloud-based services such as Google BigQuery.

For variety, NoSQL (Not-Only SQL) [62] is a new way of handling variety of data. Relational databases use rows and columns in handling data but NoSQL uses a number of other components such as giving unique key to every item in the data. Companies utilize NoSQL because it captures so many elements of supply chain that were previously only based on experience or hunches (Techterms, 2013). MongoDB – an open-source NoSQL database and other instances of NoSQL are Cassandra,

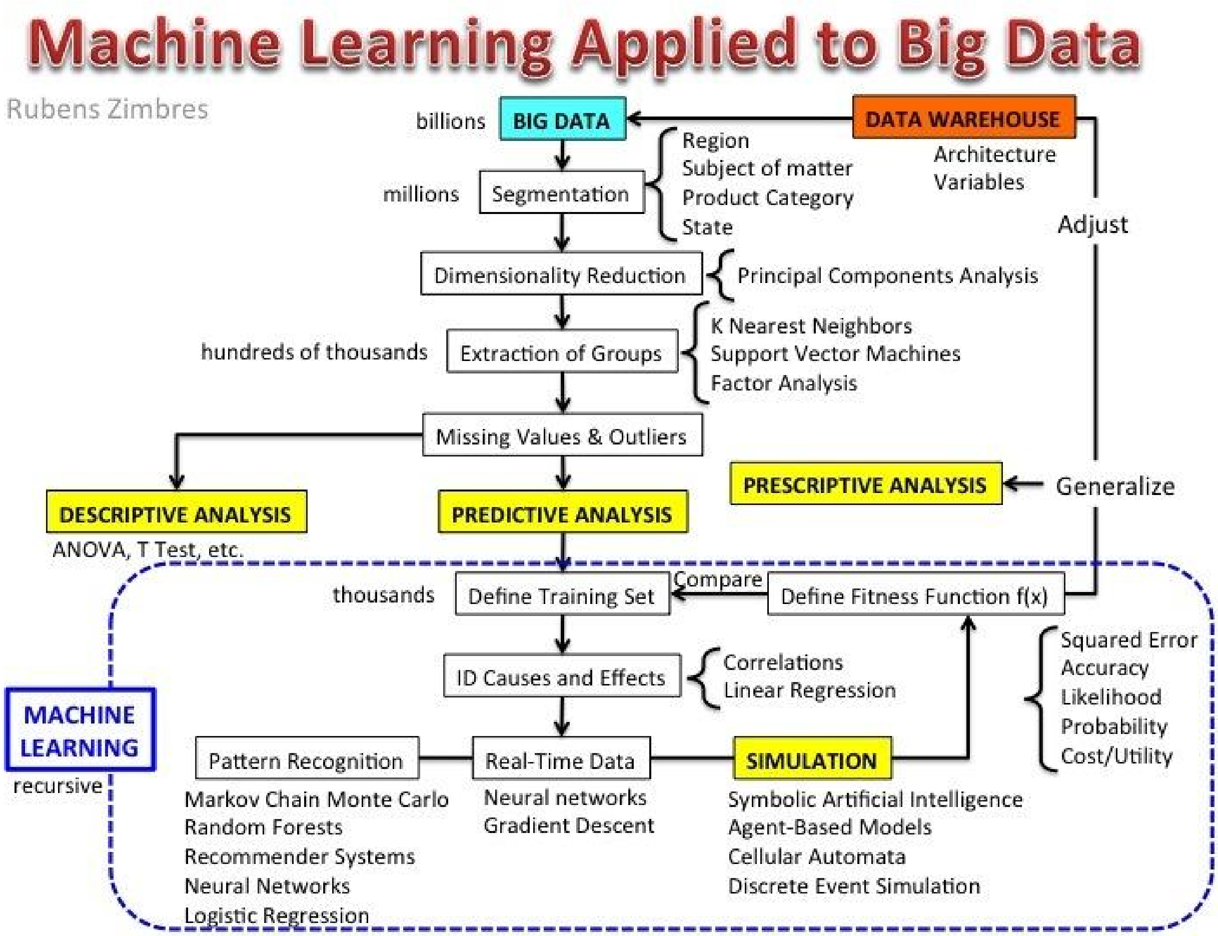
For velocity, Complex even processing or stream processing allows us to handle the velocity of time; real time generated by countless sensors involved in every bit and inch of the supply chain process can be automatically fed into stream processing which uses defined algorithms to analyze it almost instantly. Early alarm systems of supply chain would find this invaluable because red alert can be issued to company from the supply chain right when it occurs instead of giving the red alert after a sufficient time has elapsed which has given the disruption time to reckon havoc for the business. Apache spark has also been developed which is found to be around 100 times faster than hadoop for MapReduce purposes. Storm is an open-source distributed computation system designed for processing multiple data streams in real time.

For veracity, Machine learning and data mining constitute a number of models taken from mathematics, statistics and artificial intelligence that make sense of the big data as well as ensure reliability of results associated with the data so that the skepticism brought by veracity for the management can be sufficiently diminished. Also for veracity, apache mahout, machine learning in R and python are particularly useful platforms for filtering of data as well as clustering and classification of data into model points which greatly reduces having to focus on redundant data. Powerful visualizations have also covered ground to make intuitive human sense of the plethora of data and results available to us. These types of visualizations are far more flexible, representative and diverse than the usual spreadsheet based visualization tools. Instances of powerful visualization can be made through tableau, data driven documents, google interactive maps, Ggplot, Shiny and R Markdown of R and so on.

Moreover, behavioral finance has highlighted a number of ground breaking cognitive biases that human falls into; such as recency effect of seeing only the recent efforts and generalizing them to the long-term anchoring which is relying on expert opinion or the primacy effect which is giving undue importance to first impressions. Anchoring has a special context in organizations which is relying unduly on the opinion of highly paid and powerful leaders in the company. Big data can clear up the clutter of such cognitive biases by introducing data-driven decision making into the company.

Even with robust sensitive checks in place to counter over-fitting, there is still a challenge around the concepts Game Theory and the Butterfly Effect of Chaos theory and their application in insurance analytics. Modelers need to at least partly take into account these reactions within strategies to maximize the benefit and minimize any potential damages. This includes more frequently updating analysis than before to assess if there are any discrepancies between model anticipation and reality. Assessment ideally needs to incorporate horizon scanning techniques and emerging risk assessment, which can be in-built into assumptions for stochastic analysis or the robustness of sensitivity analysis [63].

An excellent illustration by Rubens Zimbres captures the synergistic interaction between machine learning and big data and is shown as a mindmap as follows:



Key thing to note here is how big data goes from billions to less and less data which is more and more refined and useful. Machine learning is then applied onto the data to arrive at actionable insights. Key models of simulation mentioned here belong to the complexity science domain detailed before. As such, this mindmap presents a powerful consolidation of many algorithms by showing relationships and links between them, as these on their own, can seem confusing and dispersed.

Along with the server clusters provisioned in company data centers or leased from virtual cloud environments, the software to deploy and manage Big Data application environments is a crucial element. The complexity of deploying "Big Infrastructure" clusters has been somewhat lessened by a new generation of open-source software frameworks. The leading solution is Apache Hadoop, which has gained great popularity due to its maturity, ease of scaling, affordability as a non-proprietary data platform, ability to handle both structured and unstructured data, and many connector products [64].

Until now, cluster management products have been mainly focused on the upper layers of the cluster (e.g., Hadoop products, including the Hadoop Distributed File System [HDFS], MapReduce, Pig, Hive, HBase, and Zookeeper). The installation and maintenance of the underlying server cluster is handled by other solutions. Thus, the overall Hadoop infrastructure is deployed and managed by a collection of disparate products, policies, and procedures, which can potentially lead to unpredictable and unreliable clusters [65].

Insurance providers are looking beyond algorithmic ratemaking techniques that are claim-centric, to ones that are person–centric. These techniques focus on analysing policyholder behavior across claims, providers, and other sources of information (e.g. how many similar claims were submitted by the same individual, reported by the same individual), and extend to data sources beyond the firewall to analytics based on external information (e.g. cohort analysis - using a person's social graph to look for similar activities among connected individuals), and considering networks of people rather than just individuals [66].

This person-centric approach requires integrating information across all providers involved in a claim, including counter-parties as well as partners (e.g. auto repair shops) requiring the schema-agnostic approach to data management mentioned earlier. Even when all the data lives within the firm, the agility provided by this approach makes it much more feasible to turn that data into useable information [67]. Telematics is the leading instance of ratemaking using such person-centric approach.

2.6.2. Big Data Application Case Study [68]

Liability catastrophes are especially rare, high impact trends that are very difficult to know in advance. Even when the evidence starts becoming more and more corroborative and certain, the insurers may not collect adequate premium as actuarial modeling using historical claims data for ratemaking. This traditional way of ratemaking on historical data can mean that insurers are potentially underwriting their own graves and selling products features that will become their own gravediggers. Asbestos is the most famous liability catastrophe that has resulted in USD 85 billion in claims in US alone and bankruptcies in 73 insurers until 2004. Consequences of liability catastrophes cab include bodily injury; property damage or environmental damage Commercial general liability insurance covers such liability catastrophes usually.

To improve our chances of collecting adequate premium so that insurers do not go bankrupt when a new liability catastrophe arises, big data tools with machine learning algorithms focused around emerging risk approach is being utilized. Framework of emerging risk is more fruitful for liability catastrophes because the impact of new technologies can be much more complex than expected, and it can take many years before the broader consequences are brought onto the surface. When a liability catastrophe does occur, the products or business practices involved are usually discontinued and the companies usually bankrupt. Hence, each new liability catastrophe is likely to happen in a different industry and in a different way. Claims data therefore characteristically cannot be used to predict the next liability catastrophe, and this presents an open challenge for actuarial modeling.

Although the world has transformed since asbestos litigation emerged, the interplay between science, technology-driven-innovation and risk which can drive the accumulation of exposure has certainly not budged. Three prominent examples of emerging risks for current times are mobile telephones causing brain tumors, hydraulic fracturing causing earthquakes and nano-materials cause lung damage, range of plastics causing endocrinal damage causing autism and obesity and so on.

The main application is text mining in a big data environment. Text parsing, sentiment analysis, opinion mining and natural language processing using deep learning algorithm can collate, identify, catalogue and track the massive universe of resources available on the internet in a data driven manner to identify key emerging risks. While the risks are diverse and too many, the means through which scientists establish causation are common to all of them. Each new hypothesis published in the scientific literature sits somewhere along the road to establishing causation, and it is possible from the algorithms mentioned here to estimate whether causation will ever be established based on the current pace at which the research is progressing.

Moreover, the data mining as well as exploratory analysis with unsupervised machine learning algorithms of scientific literature can map these emerging risks with a particular insurer given its unique portfolio which can be deduced from public sources as well now. Some companies will be located on none of the emerging risks, and some will be located on many of them – and the map itself will vary according to what is on each insurer’s list of emerging risks. Assembling companies into a portfolio and then adding up the risks across companies provides a possible method to measuring portfolio accumulation for a particular emerging risk.

These trends, mappings and probabilities can then be combined with quantitative estimates of mass litigations if these emerging risks were to occur. This show expected costs and these can vary across different industries, companies, regions and portfolios. This can serve as a vital guide for ratemaking for liability catastrophes and inform insurer on a number of key areas such as product specifications, list of exclusions, maximum sum insured, reinsurance arrangements, loading on premiums for liability catastrophes and so on. With historical analysis, insurers rely on scientific skeptics’ approach where they are not convinced of liability catastrophes until they actually surface. This is a self-defeating approach and focusing instead on pragmatism and precautionary principle can serve the solvency interests of the insurers better. Big data tools with machine learning algorithms in an emerging risk framework can better aid risk-adjusted ratemaking of emerging liability catastrophes and apply the precautionary principle to work here.

3. ENRICHING IMAGINATION: QUALITATIVE PROFILING

3.1. Overview

"The only function of economic forecasting is to make astrology look respectable" John Kenneth Galbraith

Predictive modeling and traditional ratemaking is an exercise of forecasting the future, whether directly or indirectly (indirectly as generalizing historical lessons to the future). But is such forecasting so hopeless as being same as seeing into a crystal ball?

The advantage of actuaries is their close in contact with other business professionals. That means leverage to obtain, generate and apply a lot of expert judgment to try to overcome the shortcomings of traditional ratemaking. Perhaps that is why such methods have been applied for so long.

The actuary's transition to ratemaking emerging liabilities work (and indeed any work in today's modern times) is marked less by the acquisition of new technical skills as by the adoption of new attitudes. The actuary is still a pricing actuary, but one whose conclusions are more technically realistic as well as more meaningful to upper management. The new attitude necessary is that understanding of ratemaking requires understanding of the whole [69].

The qualitative insights speak to us but generally we are too constrained within quantitative structures to make appropriate allowance for them. Some actuaries may see qualitative information as harming the objective purity of actuarial practice. However, actuaries must remind themselves that data-driven methodologies are not pure or precise; instead, they only feature an unbiased ignorance of real-world issues facing the insurance landscape [70].

Complexity science is given specific important as for ratemaking, it is important to learn the dynamics first before predicting these dynamics to hold under future.

That is not to say that we should give up any effort of looking into the emerging future as futile. What we can aim for is to develop better emotional maturity when forecasting for identification or ratemaking of any emerging liability.

3.2. Maturing our forecasting foresight [71]

Emerging liability ventures into the unknown, into open ended subjectivity. To sharpen our forecasting skills in this area we utilize the profound learning provided in the essay by Werther for SOA publication. That essay aims to help financial and insurance practitioners better recognize, assess and respond to largescale, large-impact rare events (LSLIREs), occurrences often wrongly labeled as unpredictable black swans. The learning impact from recognizing LSLIREs can be readily applied to LSLIRE emerging risks and liabilities as it is the LSLIRE emerging risks that matter most and not emerging risks that will likely have little consequence. The key techniques of pattern recognition for pattern change to identify LSLIREs are:

- **Use Multiple Methods Arrayed Around the Assessment Target:** Utilizing a diverse array of models and methods to assess emerging LSLIRE can result in reasonable level of pattern stability in normal times. However, when nearing crises, these models will fail differently but around a cluster of issues. Hence, the error term in such times is most remarkable.
- **Triangulation and Patterning Emerging Change:** When we see multiple methods going wrong differently, its' now time to narrow it down. This means establishing boundaries within which some curious clusters are morphing into new manifestations. Here, socio-psychological and historical understanding is crucial as it provides a context to the change and the reasons for it.
- **Folding In and Layering the Onion:** This is simply put, deep thinking and learning. We do have a high regard for learning and the accumulation of knowledge, but we need to have a much higher regard for the cultivation of thought. Whole world's accumulation is available on Google, but it is deep human thinking which can anticipate emerging LSLIREs. We have to avoid predetermining and study what comes, essentially applying 'active imagination'. Jung advocated what he called "*active imagination*" which is described as a state of reverie in which judgment is suspended but consciousness preserved. The key point is that the more deeply, broadly and consistently over time one folds in patterns to layer the onion, the more obvious becomes any individual pattern that does not fit. They may not fit because they are wrong, our understanding is wrong or they may be a precursor of coming system change.
- **Consider a Preference for Qualitative Insights to See Change Lacunae:** Werther suggests that a qualitative, more than quantitative, perception best illuminates a pre-event period. He argues that as stable and well-patterned systems begin to change in important ways (as their syndrome changes), it is easier to recognize this pre-change period qualitatively. Quantitatively, models are slower to respond to changes, data is limited or not credible and too heterogeneous at this time and the model results might not make much sense at emerging stage.
- **Focus on Seeing Undergirding Socio-Psychological and Style Changes:** This means essentially attacking the source. External and internal factors are far more fluid then our underlying way of doing things, our underlying socio-psychological and philosophical makeup. When normally stable qualitative psychological patterns start consistently changing, it is time for emerging new risks to be created and come up on the surface.
- **Use an Understanding of How Things and Processes are Embedded:** Learn how everything connects to everything else and how particular configurations enable or repress options and possibilities. In this matter, network theory and its application is essential.
- **Learn to Understand How Things and Processes are Entangled:** Entanglement here refers to previously one force breaking into two different forces but still behaving relatively similar. Cultures, societies, , individuals, , organizations and so forth are entangled systems: They always carry their legacy forward. They are not random, unconstrained or free, but are shape-shifting (morphing) specifics going into their future. From knowing the historical context and deep understanding we have to arrive at the entanglement features of the systems. From what did they derive, and how does this shape them going forward?

Main shortcoming of predictive modeling is that we change only few assumptions and keep rest of them constant so that they are not dynamic enough. Of necessity, any line of disciplined inquiry focuses on certain operative variables and determinants, and freezes others. Often the ground thus frozen is that very territory which is problematical from the standpoint of emerging risks.

One very powerful technique for actuaries is to utilize quantitative models and qualitative methods simultaneously. Models and statistics create discipline and uniformity for actuaries and analysts and is a powerful source for 'herding' toward similar opinions. As Carl Jung says that "the statistical method shows us the facts but does not give us a picture of their empirical reality. Actuary can use the quantitative models to arrive at the 'normal' state of opinion and use qualitative, deep and context specific explanations to understand and explain deviations from the normal standards.

One aspect of quantitative models is particularly useful before emerging LSLIRE arise is breaking down of models and increasing diverge between stories of analysts explaining these deviations. More analysts will start feeling that something is wrong but cannot identify through their mainstream models what is wrong specifically.

3.3. Concerns with Big Data [72]

Ronald Coase said 'If you torture data long enough, it will confess to anything'. With the advent of big data and its accompanying curse, we do not need to even torture the data.

MIT's top-ranked Alex Pentland provides nuanced views that enhance the potential for better LSLIRE recognition and assessment. First, "The data is so big that any question you ask about it will usually have a statistically significant answer. This means, strangely, that the scientific method as we normally use it no longer works."

Unfortunately for this big data insight, the scientific method as we normally use it never did work well for even normal whole system change recognition, and especially not for rare event foresight, for the simple reason that just because something formerly couldn't be measured didn't make it irrelevant. Recall Kant's, Jung's, Berlin's, Einstein's and Goethe's "beyond analysis" critique and advice: Intuition—experience and familiarity—links knowledge to understanding.

Nassim Nicholas Taleb says that 'the more data we have, the more likely we are to drown in it. 'Fooled by Randomness (2001). Likewise, Werther makes an amazing assertion when he says that lacking the human inputs of correct intuition, imagination and understanding, technical knowledge management approaches like "big data" is only about getting better paint and brushes (tools). Likely, they will yield greater confusion and crises. "*Mastery yet needs better painters*."

The core learning point is that quantitative modeling constructions typically fail when needed most, when something is actually changing. Qualitative profiling can help us better at sense and responding to change. Werther concludes that until and unless we consider intention—philosophy, cognitive system, bias, etc.—used in building data, models and expert's analysis, and implications, we are missing the big picture already. Nietzsche's point that "the decisive value of an action may lie precisely in what is unintentional in it. … The intention is only a sign and a symptom, something which still needs interpretation, and furthermore a sign which carries too many meanings and, thus, *by itself alone* means almost nothing" (emphasis added).

Once the models are generated using agent based modeling, qualitative profiling etc it is necessary to interpret even the results from sociology of finance perspective, with philosophical maturity and not merely with common sense. Lastly, an open and inquisitive mindset is most necessary for accurate forecasts as 'superforecasting' emphasizes and shows.

Appendix B from B1 to B4 brings philosophical maturity and basic sociological awareness within the ratemaking actuary. While they can be termed as not directly relevant, they are crucial for the actuary to develop basic qualitative profiling skills and see ratemaking and emerging research in its bigger picture without isolating the analysis to only quantitative modeling. It comprehensively details sociology of finance, how risk and life insurance functions in a social context. Selected excerpts by Francois Ewald and Aradau et al are included that deal with the philosophy of insurance operations and companies. This is followed by an anthropological explanation behind one of the most vexing problem for General Insurance actuaries, namely the underwriting cycle. The breath-taking insights from these sections, and their precise explosive writing makes the author of this report wish he had read them six years ago when he started out as an actuarial trainee.

3.4. More Strategic Notes

In the Black Swan, Taleb describes "Mediocristan," (Quadrants I and II) as a place where Gaussian distributions are applicable. By contrast, he calls Quadrant IV "Extremistan." It is Extremistan where we are interested for understanding complex systems. Actuaries like to build their models on the Gaussian distribution we are perhaps avoiding professional expertise by fooling ourselves by retreating to the comfort and safety of the womb of Mediocristan instead of facing Extremistan in all its unknown mystery and ambiguity [73].

To avoid being ambiguity averse, we can train ourselves to explore the unexplored. As actuaries, perhaps we could make a greater effort to uncover hidden patterns. Actuarial and statistical modeling is a double-edged sword. If applied correctly, it is a very powerful and effective tool to discover knowledge in data, but in the wrong hands it can also be distorted and generate absurd results. It is not only our results that can be absurd, but our risk-averse and ambiguity-averse mentalities as well [74]. As Voltaire said "doubt is not a pleasant condition but certainty is absurd."

This teaches us that we should be aware that precision implies confidence. We must be very alert to not fall into this trap. While point estimates are often required (we have to quote and file a specific premium), there are many cases where ranges of estimates are more appropriate. While statistical techniques can sometimes be used to generate precise confidence intervals, mostly statistical rigor is not possible or even necessary for emerging risks. By discussing a range of estimates, actuaries can provide more value to their stakeholders by painting a more complete picture of the potential impacts of decisions related to emerging liabilities [75].

Finally, we must ensure that actuarial output highlights fundamental questions at hand to stakeholders instead of confusing them with complicated numbers and lack of decisiveness. There is obviously a premium to be established but the management running the company does not care what the actual premium is—they need to know the likely impacts of that premium on the business. From a financial perspective, we should avoid saying that we've priced for a certain margin because that exact margin is, in the end, going to be exactly wrong! The better approach would be to explain the range of possible outcomes and the impacts of each [76]. As Nassim Nicholas Taleb explains: "There are so many errors we can no longer predict, what you can predict is the effect of the error on you!"

In conclusion, this is an exciting and dangerous time for the ratemaking actuary in particular and for actuaries in general as well. The proliferation of big data, machine learning techniques and evolving of emerging risks at lightning speed has resulted in problem-solving means and aptitude which we have been previously unable to tackle, but the same advances have brought analytical professionals from other disciplines into spaces traditionally led by actuaries as well as its own share of technical challenges [77].

4. CONSOLIDATIONS & CONCLUSIONS

In this report, we have attempted to creatively synthesize the many pluralistic approaches to ratemaking for emerging liabilities as well as synergistic interpretation of findings of these pluralistic researches. The core two areas were better technical tools and more pragmatic mentality. The reader will be the judge of whether we succeeded or not.

We can recognize that though we cannot precisely predict black swans but forecasting emerging liabilities and their ratemaking can be a professional-character building experience in itself where we train to be better evolvers rather than better predictors alone [78].

We can highlight that while recognizing facts (in form of quantitative analysis), it seems as if we only tend to scratch its surface as data, on its own, highlights results; whereas there are plenty of processes that culminate in data generation as well as modeling methodology in the first place. There is an incredible depth once when we start looking beyond the facts into fact-making itself; and this is where expert judgment and qualitative profiling can prove invaluable to guide the ratemaking exercise.

Agile Risk culture is foremost for any ratemaking exercise because financial and insurance sector is not solely run by quantitative numbers, but by the underlying human psychology as well. It is up to the risk culture to not antagonize in binary opposites like complex/simple, good/bad etc., but to reach the middle ground to converge communication and mentalities between different stakeholders.

In the end, it is useful to keep a few sobering meditations in mind:

- We suffer too profoundly even from small data glitches.
- Better than many complicated equations are few statements that give clarity to shareholders
- The experience of all deep datasets is slow. They must wait long until they know what has fallen into their depths. Machine learning can lower that waiting time.
- Generally, there is either over-reliance on data and models or negligible reliance on them. We have to be familiar with the golden mean that resides between two vices. So here our data and modeling orientation should be in between the extremes of reliance on only opinions and only data and models.
- Unless one considers intention—philosophy, cognitive system, behavioral bias, etc.—used in building data, models and expert's analysis, and implications, one can be missing the big picture already.
- Provide historical data to limit the amount of work required for attaining a context for the data but data should be adjusted to reflect current conditions, not historical circumstances [79].
- Focus on developing a ratemaking plan, not numerical premium and projections only [80].
- Know your context [81].
- Beware of qualitative shifts [82].
- Know how the model results will be used [83].
- Do not anthropomorphize models. Anthropomorphism is the tendency to characterize animals, objects, and abstract concepts as possessing human-like traits, emotions, and intentions. Models

are not reality or real human social behavior. At best models are idols [84]; at worst, a distraction and cause for herding.

In conclusion, it is hoped that this review was able to lead to a better understanding of the inherent realities and trends in ratemaking for emerging liabilities and compels us to view this exercise holistically so as to bear more fruitful results. It is also meant to contribute fruitfully to the current existing dialogue on identifying and ratemaking for emerging liabilities.

Appendix A- Quantitative tools

Appendix A1- Game Theory Applications to Ratemaking [85]

Most insurance markets can be considered as oligopolistic. Such markets can be effectively investigated through game theory. Insurance companies also usually execute strategy by setting price first through risk quantification and then customers decide whether to buy. There is an area of negotiation between insurers and customers but the negotiation usually lies between the costs and commissions loadings of the premium loading instead of being lower than marginal cost (here burning costs/pure premium).

Strategic decisions have to take other competitors' reactions into account in order to thrive in an oligopolistic setting as its common in insurance sector. Game theory provides useful tools and frameworks to do this. Here we apply game theory to setting general insurance prices while taking reactions of competitors into account.

Game theory is the study of strategic decision making. More operationally, Roger Myerson defines it as "the study of mathematical models of conflict and cooperation between intelligent rational decision-makers. Game theory provides general mathematical techniques for analyzing situations in which two or more individuals make decisions that will influence one another's welfare." (Myerson, 1991). The core idea of game theory is to determine the expected payoffs for each player under each option and for each choice made by the other players. Rational players will be aware of their alternatives, form expectations of any unknowns, and will choose their actions deliberately so as to maximize their expected payoff.

There are a wide variety of game theory models but for ratemaking purposes, here we will highlight two methods for insurers' tendencies; Cournot-Nash Model and Stackelberg Model. For consumers' tendencies, we will also highlight two models of Bertrand price competition model and hotelling's model for differentiated products. Later in the Gamification section, we will also briefly touch upon Cournot-Nash Model and Stackelberg Model.

Cournot-Nash Model is where an insurer takes its individual decision based on accepted underwriting risk no matter what the opponent charges. On the other side, the Stackelberg Model is based on a leader-follower approach, where the competing insurer has a strong tendency to make a strategic decision based upon the market maker's position.

In general insurance ratemaking, these two models can be seen to be applied simultaneously. For the burning cost or pure premium, which is the individual insurer's unique break-even point and minimum premium, there is no consideration of taking the competition into account to reduce prices lower than its own burning cost. However, there are various loadings above the burning cost such as profit loading, administration cost loading, commissions loading etc and this is where insurers look and compare to other competitors to make sure that they are competitive to the consumers.

Moving on, the Bertrand price competition model shows that in a competitive market where consumers select products based solely on the criteria of prices, the equilibrium will occur where price is equal to the marginal cost, where there are only two firms and both have the same costs. This model generates the Bertrand Paradox which is that it takes only two firms to obtain perfect competition of Marginal Revenue being Equal to Marginal Cost with zero loading for profit.

Hotelling's model adds another dimension to Bertrand's model to increase realism of modeling as it allows for differentiated products and the fact that some purchasers of a product will buy from one seller and others from another seller in spite of differences in price.

There is no Bertrand Paradox with differentiated products. When the products are more differentiated (i.e. larger k) then prices are higher. When $k = 0$ then the model approaches Bertrand competition with homogeneous products. To make things more realistic, where costs differ between firms, then the equilibrium price will be some weighted average of the costs and k. An intuitive interpretation of k is that it is the amount in excess of the price charged by other sellers that a firm's most ardent supporter is willing to pay for that firm's product.

An important conclusion is that the equilibrium premium is higher than the expected claim (marginal cost), which is different to the Bertrand model, where the equilibrium premium is equal to the marginal cost. This suggests that there is a direct relationship between the consumer preference location concept used by Hotelling and the price elasticity used in this model. The level of equilibrium premium depends on the elasticity of the market, for example the lower the elasticity then the higher the equilibrium premium. No cooperation between insurers is needed to achieve that. Thus, insurers in ratemaking, should not only focus on keeping their prices competitive, but also focus on differentiating them from the rest through brand recognition, superior customer service, additional features, and guided innovation and so on.

Appendix A2- Gamification [86] [87]

A reasonable definition of Gamification is that it is the application of game elements and game design techniques to solve real world problems— serving a purpose that is outside of the game.

Currently, insurers are using the strategy of Gamification to improve their market penetration through educating the end user. In life insurance, the aim so far has been to reduce the complexity of life insurance products to the users. In general insurance, the end user is shown how insurance can save his tangible assets in stressful times. For instance, Farmville and Cityville virtual games have virtual general insurance provided by brand name of a real insurance company of "Farmers Insurance Group" and players discover while playing, the benefits of their insurance once adversity strikes.

Aside from computer based virtual reality games, telematics is a very powerful real-world gamification situation. A telematics enabled device is plugged into the vehicle, collecting data on acceleration, deceleration, braking, and rules violation and storing it in the insurer's database. There, it is used to calculate a specific score relative to the driving characteristics of the driver by ratemaking based on latest tools like machine learning algorithms etc. This score and the associated data can be used by the insurer and employed to offer rewards such as premium discounts for people with better driving skills. With this real-life gamified strategy, people tend to drive more carefully in order to earn more safe driving points and then more premium discounts. Though discounts are given as rewards, in the long term the approach will reduce the number auto claims, improving the insurer's profitability.

Another interesting example relates to home insurance. HCL has developed an innovative gamification for home insurance where a virtual agent takes the user through a simulated house with living room, kitchen, bed room, kids' room, ward robe etc. Each room is fully furnished in high detail and the user can choose which room the agent has to move in and pick the item for insurance. When the item is picked it gives voice and text information on maintenance tips. Once the items are selected, it gives the quote instantly and also helps to get discount if player chooses to take up a simple game on the maintenance tips and answers correctly.

These powerful examples show that ratemaking in such a dynamic gamification is not just a passive one-sided exercise by the insurer but is a connecting bridge from insurers to the policyholders and effectively serves to modify policyholder behavior, instead of only modeling it.

With the rise of the next generation of millennials, gamification is becoming increasingly important. 57% of the uninsured world population is in age group 18 – 44 where 61% of this age group plays games and 65% uses their handheld to play the games. So, gamification can cause a larger portion of the 57% of the uninsured to experience dynamic ratemaking processes which influence millennial policyholders' behaviors to mold frequency and severity of claims into the insurer's favor.

Gamification can also help insurance business teams and employees to train them faster and better. This can increase chances of sales teams giving the right discounts and pricing for large and fast deal closure.

Appendix A3- Fuzzy Logic [88]

There is a myriad of ambiguities and uncertainties in the information we receive decode and signal which tends to limit the functionality of traditional methods that are based on crisp logic. For instance, while USD 500 premium means you will have to give USD 500 to purchase the policy, the opinion whether this premium is adequate for the insurer or not, and reasonable or too expensive for the consumer is quite subjective. Fuzzy theory is developed to overcome this insufficiency by taking account of ambiguity in information. A number can be crisp as well as fuzzy, which recognises the 'degree of truth'. In doing so, set theory, which is the groundwork of probability theories, is transformed into fuzzy set theory and all following applications are updated to be able to integrate fuzziness.

When using fuzzy logic, people's qualitative description as well as quantitative estimation can be elaborated to maximise its utility. Fuzzy logic offers a more natural language, a way to deal with imprecise or incomplete data, and a way to group items together so that complexity is reduced, rule sets can be smaller, and speed of solution can be increased. This is extremely crucial for ratemaking emerging liabilities because they face lack of data, are time sensitive and need sound qualitative inputs to profile the complexity of the emerging situation.

Fuzzy Logic can be a useful way to improve many actuarial models especially when ratemaking for emerging liabilities:

- It can be a closer match to the way humans think.
- Linguistic variables introduce both clarity and flexibility.
- Fuzzification can handle incomplete and inconsistent data.
- Rules sets can be cleaner and fewer in number.
- Defuzzification produces quantifiable results.

This is not to say that fuzzy logic systems are not without their shortcomings. In the application of fuzzy logic systems to risk assessment and risk decision-making, many practical issues and challenges can be encountered. Even with a solid theoretical foundation, the success of a system depends on many factors such as the quality of the experts' opinions, the system's own credibility and its linkage to management decisions. It can aid deep and sound thinking but cannot replace it.

Fuzzy logic models can also be used with other models such as decision trees, hidden Markov and Bayesian and artificial neural networks to model complicated risk issues like policyholder behaviors. A risk assessment and decision-making platform for ratemaking built on a fuzzy logic system can provide consistency when analyzing risks with limited data and knowledge. It allows people to focus on the foundation of risk assessment, which involves the cause-and-effect relationship between key factors as well as the exposure for each individual risk. Rather than a direct input for the likelihood and severity of a risk event, it supports human reasoning from the facts and knowledge to the conclusion in a comprehensive and reliable manner.

Appendix B- Theoretical Qualitative Understanding

Appendix B1- Sociology of finance

Introduction

Emmanuel Derman, a leading quant, advocates that there is enough mathematics in finance already; what we need is imagination [89]. Perhaps this void can be filled by sociology of finance.

Sociology of finance is defined as "the systematic study of financial markets and transactions from a sociological perspective. The goal is to develop a rich and in-depth understanding of the financial markets from an interdisciplinary perspective." [90]

Many disciplines and professions other than sociology can gain from a better understanding of social aspects of finance such as those in the economics and finance fields. The aim of this report is to investigate various sociological ideas, concepts and applications to finance. These areas are quite broad, distinct from each other but it is imperative to discuss these so as to have an in depth understanding of the various paradigms of sociology of finance. These concepts are grouped in the following sections in this report;

1. Cultural construction of finance
2. The social-constructive cognitions of financial analysts
3. Financial engineering and the financial crisis

Cultural constructions of finance

Cultural construction as per Suttles linguistic research on the use of the word 'economy', Suttles discovers that the modern usage of the word 'economy' as a system of exchange, production and consumption was not existent in 1929 crisis and only assumed its modern usage when Keynes introduced it in 1934. The 1929 crises were seen as a crisis in business, not the economy and the social metaphor used to describe it was 'business' (instead of economy) which was a natural occurring activity which was self-correcting but sometimes sick as well. Over the next few decades this metaphor changed and now the economy was viewed as a 'grand machine' that can be controlled by social engineering of economic and social policies. By 1987 and onwards, embezzlements, shady products, deregulation, massive innovation in products and technology meant that the economy had become a 'casino' [91].

Starting from 2008 financial crises and onwards, economy is primarily thought of as a computer network or information system. The *viruses* of default *freezes* credit and spread throughout global *networks* which *crashes* the economy [92]. These metaphors increasingly bring the fragility and vulnerability of the economy onto the surface to make us realize that we live in a 'risk society' (Ulrich Beck) where risk is globally being created and leads to massive scales of crashes in the economy [93].

These shifts in the core metaphors point towards ideological shifts. Such shifts occur most abundantly in times of crises where uncertainty reigns supreme and institutional guides to behavior are no longer relevant. It is in such times that metaphors pack the uncertainties in a symbolic manner to guide the people like a map in an unknown territory [94].

Financial crises are also symbolic and ritual events. Financial crises arise with an apocalyptic anxiety that something we never predicted happened and is causing the end of our world as we know it. Over time, this initial anxiety transforms into passiveness of 'learned helplessness' (Martin Seligman [95]) which teaches us that we have no control over these external torments and this leads to pessimistic outlook of the society at that point in time. There is also 'atoning' or repenting where the public rage over accountability forces the parties responsible to at least acknowledge their role in the crises and what they did wrong [96].

Another key concept in sociology of finance is time-space compression. Due to globalization in the post-modern era, we continuously face 'time-space compression' in finance. This refers to increasing capacity of capital to be available and transmitted across geographical barriers within moments and not delayed by time. This has been brought possible by globalization and technological advances. But this bridging of time and space has proceeded in a highly unequal manner. As time-space compression increases the power of global capital centers like Wall Street and city of London, others offering fewer opportunities for profit have continuously found themselves pushed further away in relative economic continuum [97].

Time space compression along with other social trends towards polarization means that there is not just increasing economic inequality but also social and cultural differentiation. Oxfam officially showed that now top 1% own more than the remaining 99% [98]. We also have historically high gini coefficient which is a metric for measuring economic inequality. We are witnessing the development of differential modes of treatment of populations, which aim to maximize the returns on doing what is profitable and to marginalize the unprofitable. Instead of segregating and eliminating undesirable elements from the social body, or reintegrating them more or less forcibly through corrective or therapeutic interventions, the emerging tendency is to assign different social destinies to individuals in line with their varying capacity to live up to the requirements of competitiveness and profitability.

Taken to its extreme, this yields the model of a 'dual' or 'two-speed' society recently proposed by certain French ideologists: the coexistence of hyper-competitive sectors obedient to the harshest requirements of economic rationality (we can see this today in P & C sector), and marginal activities that provide a refuge (or a dump; social impact bonds; rising charity initiatives all over the world etc.) for those unable to take part in the circuits of intensive exchange. In one sense, this 'dual' society already exists in the form of unemployment, marginalized youth, the unofficial economy. But until now these processes of disqualification and reclassification have gone on in a blind fashion. They have been uncontrolled effects of the mechanisms of economic competition, underemployment, adaptation or non-adaptation to new jobs, the hemorrhaging of the educational system, etc. The attempts which have been made to reset these processes are more addressed to infrastructures than to people: industrial concentration, new investment sectors, closures of non-competitive concerns, etc. - leaving their personnel to adjust as well they may, which often means not particularly well, to these 'objective' exigencies [99].

The social-constructive cognitions of financial analysts

Financial analysts are conceptualized in sociology of finance as organizational and institutional agents. They regularly maintain hegemonic categories for valuation of financial entities focusing primarily on shareholder value perspective [100].

The core process of valuation of fundamentals for equities is to estimate some value indicator for the concerned company and relate this indicator to the market price. The difference between such fundamental value and market value then reflects whether the company according to the analyst is over-valued or undervalued [101].

Aside from a micro-company wise analysis, whole markets and sub markets are also analyzed to forecast the valuation dynamics of whole markets. Why is such analysis undertaken? This is because analysts recognize that market prices can and do swing far away from fundamental valuations over long term as well (and not only short term). This is due to a number of sociological workings in the financial markets. Analysts recognize the limits of our rationality and the asymmetry of information. Not everyone is an equal participant in the market and the spotlight is always fixed upon the market movers, the deep pocketed investors that seek alpha returns and create a path for market followers to follow through index tracking. Another important concept, long discussed by philosophers and sociologists is that of reflexivity. Reflexivity says that we are not just micro agents subject to an all-powerful macro market. While the market does lead to individual action, a collection of individual action, thinking and biases can also change the market and the fundamentals that assist in determining the market prices itself [102].

As a result of these asymmetries, a core suite of analysis is 'comparative' and 'precedent' analysis which goes on to show that analysts continuously observe each other. Moreover, the use of term 'market expectations' highlight the analysts' consensus prominently. These consensuses are published by specialized information providers such as Bloomberg and Reuters regularly.

These consensuses are utilized by analysts both when homogenizing their forecasts with these as well as when differentiating their forecasts with regard to the consensus. These consensuses are used as an 'anchor' to situate their forecasts in context of the market as well as to identify market surprises because of some factors that the consensuses have under-valued or ignored. These surprised divergences from the market view are based mostly on fast and frugal heuristics [103].

Due to multiple irrational factors in work, a tension or 'cognitive dissonance' is created between the cognitive anticipations of the analysts on how market prices really work and the 'fair' fundamental value of equity. This tension is managed by differentiating the short-term basis from the long-term outlook. Long term outlook is treated as quite differently than short term on the belief of mean reversion which is that in the long term, values will converge to the fundamental values [104].

Aside from technically seeing market objectively, storytelling is also central to the practices of analysts. Selective drawing on qualitative as well as quantitative information in modeling and in their narrative, is developed in order to tell a story about the company to investors and other parties involved with less technical aptitude. The stories are a logical progression that aims to make sense and is vital as they absorb differing, heterogeneous, irrational, intuitive information, connect the various dots such as connecting past and expected future with the present, and are explainable in common sense manner to other investors. These stories facilitate analysts' communications with clients, arouse and influence trading and increase status differentiation within the various levels of community of the analysts [105].

But these sociological elements underpinning daily realities of analysts are not without its drawbacks. The analyst consensus can lead to withering away of the diversification benefit as if many traders lead a similar position on the market, the elements in the variance-covariance matrix that are uncorrelated or weakly correlated can suddenly become highly linked. This is what caused LTCM's diversification to fail in the first place as many other traders took on same or similar positions as LTCM was viewed as a winner. These consensuses can and do play their role in perpetuating herding behavior and group think where too many similar thoughts and actions lead to a boom or a bust in the financial markets.

Financial engineering and the financial crisis

Finance as per sociology is studied as a 'field' of markets, government, firms and financial products. The field concept recognizes that these elements take each other into account and are interconnected. This way of looking at finance like a field enables a holistic view that can potentially peak into the bigger picture involved.

The social context to proliferation of advanced financial engineering theories can be holistically elaborated. The first wave of developments in modern portfolio theory concerned itself with re-affirming investment practices and wisdom, such as know your business, do not put all your eggs in one basket etc, using mathematical language. Theories such as those of Markowitz and Roy, and Modigliani and Miller are instances of this wave [106].

The second wave was more ambitious. A deeper economic context was added to the mathematics to devise new theories which portray a discrete jump over the first wave which was created mainly to validate existing investment practices in order to increase penetration of financial engineering to the business and investment communities. Efficient market hypothesis and Capital Asset Pricing Model fit the bill for this wave [107].

Amidst this wave, a number of macro-economic changes ushered that led to increased demand for financial engineering. Fall of Dollar from the gold standard in 1971, high inflation, and fluctuations in commodities lead to rampant volatilities in the financial markets. This is when the Black-Scholes formulation of valuing contingent payoffs made it into the lime light as a way to price derivatives that were increasingly used to hedge against these volatilities. Ironically, the very instruments made to reduce risk lead to a financial meltdown due to the institutional manipulation of such products.

But these financial models over time did not just describe the models, they transformed them as well. Owing to the huge importance these financial models gathered in the markets, they were now creating reflexivity by transforming markets after their own images [108].

Derivatives such as modeling-intensive Mortgage Backed Securities and Credit Default Swaps are widely credited with being one of the main reasons for the financial crises of 2008. It was believed that these allowed for widespread diversification of risks, whereas the financial crises showed that it did not lead to diversification of risk as much as its wholesale transfer to others. It was the confounding modeling complexity surrounding these contingent cashflows of MBS and CDS that meant that no one properly understood them and it enabled the transformation of even the riskiest of mortgages into investment grade securities [109].

While this is true, the explosion of these instruments around nonconventional mortgage securitization was also, at its core, a product of the structure of sociological relations between firms and the state in the market. Even though quants were used to justify MBS, MBS were not made by quants themselves. This central feature of all MBSs was thus not the creation of financial economists but employees of financial firms who were trying to overcome the objections of potential customers to buying bonds [110]. By focusing primarily on the innovative financial instruments themselves, we miss the context in which these instruments emerge and assume importance.

The banking strategy over time shifted from long term retail basis to fees-generating model for revenues. MBS were highly profitable as well as large in size which allowed for massive fees to be generated. Couple this with increase in leverage being used to further increase profits, and mortgages sold even to the riskiest of customers to increase revenue, MBS were utilized to further institutional greed. Also, the fact that regulations barred the Government state entities from issuing and guaranteeing these risky subprime MBS, an alternative means to issue security and make the investors comfortable with these products had to be devised. Here is where the quants figure in. Quants with their complex statistical models and authoritative scientific feel replaced the traditional government guarantees to convince risk-averse investors to buy these products [111].

No matter how aggressively the banks tried to model financial markets and products, they had shortcoming in their assumptions and on the fact that no business is separate from its market context and realities. Thus, even the most sought after models such as Value at Risk, Black Scholes etc. broke in face of risky bad marketing and selling. All models that previously gave solid results melted into air.

Government was also complacent in a number of ways as a religious and almost fanatic belief over the efficient markets hypothesis stifled any initiative to increase regulation (Noam Chomsky [112]). Secondly government was always few steps behind the product innovations and market trends. Alan Greenspan famously testified before Congress that he did nothing to halt the rapid growth in subprime mortgages as he believed that the banks would not have given the loans if they were deemed to be too risky [113]. Such thinking reflects undue belief in the capacity of markets to be self-correcting.

Conclusion

To summarize, we looked briefly at how finance is culturally constructed. We also elaborated on the micro choices financial analysts make in part of their daily lives in the hegemonic structure as well as seeing toxic structured products in their proper social context.

Appendix B2- Philosophy in Insurance

These are perspective-changing and incredibly invaluable excerpts from the essay 'insurance and risk' by the philosophy Francois Ewald [114]. In the end, terrorism extract is given. In few pages Francois is gracefully able to explain the underlying mechanisms that take a whole life to experience and realize.

"Insurance designates not so much a concept as an abstract technology. Using the vocabulary of the nineteenth-century actuaries, economists and publicists, we can say that the technology of insurance is an art of 'combinations'. Not that insurance is itself a combination, but it is something which, on the basis of a technology of risk, makes possible a range of insurance combinations shaped to suit their assigned function and intended utility-effect. Considered as a technology, insurance is an art of combining various elements of economic and social reality according to a set of specific rules.

The particular form insurance technology takes in a given institution at a given moment depends on an insurantial imaginary: that is to say, on the ways in which, in a given social context, profitable, useful and necessary uses can be found for insurance technology. Thus, the birth of social insurance at the end of the nineteenth century needs Insurance technology and actuarial science did not fall from the mathematical skies to incarnate themselves in institutions. They were built up gradually out of multiple practices which they reflected and rationalized, practices of which they were more effects than causes, and it would be wrong to imagine that they have now assumed a definite shape.

Insurance can be defined as a technology of risk. As a technology of risk, insurance is first and foremost a schema of rationality, a way of breaking down, rearranging, ordering certain elements of reality. The expression 'taking risks', used to characterize the spirit of enterprise, derives from the application of this type of calculus to economic and financial affairs.

Rather than with the notions of danger and peril, the notion of risk goes together with those of chance, hazard, probability, eventuality or randomness on the one hand, and those of loss or damage on the other - the two series coming together in the notion of accident.

The insurer's activity is not just a matter of passively registering the existence of risks, and then offering guarantees against them. He 'produces risks, he makes risks appear where each person had hitherto felt obliged to submit resignedly to the blows of fortune. It is characteristic of insurance that it constitutes a certain type of objectivity, giving certain familiar events a kind of reality which alters their nature. By objectivizing certain events as risks, insurance can invert their meanings: it can make what was previously an obstacle into a possibility. Insurance assigns a new mode of existence to previously dreaded events; it creates value:

Insurance is one of those practices linked to what Pascal called the 'geometry of hazard' or 'algebra of chances ' and is today called the calculus of probabilities.

The mutualities created by insurance have special characteristics: they are abstract mutualities, unlike the qualitative mutualities of the family, the corporation, the union, the commune. One 'belongs ' to the latter kinds of mutuality to the extent that one respects their particular duties, hierarchies, orderings. The family has its rules, the trade union its internal regulations. These mutualities place one, moralize one, educate one, form one's conscience. Insurance mutualities are different: they leave the person free. Insurance provides a form of association which combines a maximum of socialization with a maximum of individualization. It allows people to enjoy the advantages of association while still leaving them free to exist as individuals. It seems to reconcile those two antagonists, society-socialization and individual liberty. This, as we will see, is what makes for its political success.

Insurance does not, as has been mistakenly said, eliminate chance, but it fixes its scope; it does not abolish loss, but ensures that loss, by being shared, is not felt. Insurance is the mechanism through which this sharing is operated. It modifies the incidence of loss, diverting it from the individual to the community. It substitutes a relation of extension for a relation of intensity.?

As Proudhon explained:
The savings bank, mutuality and life assurance are excellent things for those who enjoy a certain comfort and wish to safeguard it, but they remain quite fruitless, not to say inaccessible, for the poorer classes. Security is a commodity bought like any other: and as its rate of tariff falls in proportion not with the misery of the buyer but with the magnitude of the amount he insures, insurance proves itself a new privilege for the rich and a cruel irony for the poor.

Insurance possesses several distinct dimensions of technique. In the first place, it is an economic and financial technique.

Secondly, insurance is a moral technology. To calculate a risk is to master time, to discipline the future. To conduct one's life in the manner of an enterprise indeed begins in the eighteenth century to be a definition of a morality whose cardinal virtue is providence. To provide for the future does not just mean not living from day to day and arming oneself against ill fortune, but also mathematizing one's commitments. Above all, it means no longer resigning oneself to the decrees of providence and the blows of fate, but instead transforming one 's relationships with nature, the world and God so that, even in misfortune, one retains responsibility for one's affairs by possessing the means to repair its effects.

Behind this problem of guarantees there lies another, profounder one, namely the problem of the permanence of insurance institutions. Since they are supposed to be providing security, these need to have a quasi-infinite longevity. With insurance one comes to experience a sort of dilation of timescales, stretched out to span not just one generation or lifetime but several, and thus positing the survival of society for an indefinite future. One moves from a limited conception of time bound to the life of individuals, to a social time measured against the life of society, actualizing the Comtian conception of progress which founds the idea of solidarity as formulated in the political theory of solidarisme. In guaranteeing security, the state is equally guaranteeing itself its own existence, maintenance, permanence. Social insurance is also an insurance against revolutions."

Selected excerpt from terrorism insurance by Aradau et al are [115]:

"What interests us is not so much these technologies per se, but rather what political imaginary makes them possible and what political imaginary they enact. Insurance starts by classifying and objectifying phenomena in order to be able to calculate the degree of chance or risk. Insurance has its own science, actuarialism, which claims to be able to assess risks in order to commodify them (Ericson et al., 2003: 8). The first imperative of insurance is to define. The insurance industry needs to define terrorism, create a calculable rendering of terrorism and constitute the subject who is to be insured. For even when the mathematical calculus of probability finds itself surpassed by catastrophic events and other means of governing more akin to the game model are proposed, insurance still relies upon classifications and definitions of what and who is to be insured. The other imperative of insurance is to represent the future and its relation to the present. In attempting to neutralize or even prevent the possibility of 'dangerous irruptions' (Castel, 1991) in the future, insurance also colonizes the future."

Appendix B3- Sociology of Risk and Other Areas

Sociology of risk [116]

A number of key insights on sociology of risk have been elucidated by the previous sections. Here, we emphasize that although sociology of risk attracts a lot of research activities, it is important to categorize it according to their core ideas. The three main categories are:

- risk in (rational) decision-making,
- risk in calculative-probabilistic calculation and
- risk as part of a modern worldview.

Different sides to the epistemological status of risk can be shown with following different approaches to sociology of risk. The early cultural approach argues that while risks are real, they are socially constructed by the particular configuration of a society with its members and external factors. Chiefly, how risks are selected and prioritized is politicalization of risks achieved by key institutions in the society.

From the radical constructivist perspective of governmentality and systems theory, we deduce that risks are not created, they are manufactured and proliferation of risks can serve very different purposes than what appears on the surface. Objective probability and statistics is applied to create a new field of knowledge and specialists which have more power than other laymen. This 'bio-politics' quantifies calamities and individuals into age, happiness, gender, health status, frequency and severity and in the process creates a powerful system of governing, controlling and surveying the population. In this surveillance society, growing concerns about risk are not a result of the quality of risk or a specific culture but of how the liberal societies are actually governed.

Systems theory pictures society as existing in its communications and so risk is a way of communication and discovering for the agents in the society. There is conflict based framework of society and social risks arise because some groups create and divert risks to other parties as externalities to avoid any blame or reprehension. Gains are however privatized and remains within the powerful groups. Systems theory sees growing risk communication as a result of ongoing economic inequality and societal differentiation, which fuels negotiations about who is responsible for undesired societal events and increases chances and sharpness of direct confrontations. (Luhmann 1993; Japp and Kusche 2008).

Finally, Beck emphasizes that new risks are increasingly threatening modern civilization. Aside from natural catastrophes, man-made manufactured risks are now larger than ever before and it is becoming extremely hard to even quantify their impacts.

As can be seen, the governmentality approach can be seen as very relevant to actuarial practices. It is argued that group differences created by historical processes of domination are demoralized by actuarial representations (as they are for instance in insurance premium setting) it becomes more difficult for disadvantaged groups to generate political power. This is because sensitive stratifications like gender, credit profiles and pricing elasticities etc are living realities of the people whereas in classification for actuarial ratemaking, they are stripped off their subjectivities and transformed into an objective formal reality. The moral charge carried by these forms of differences are eliminated and so actuarial ratemaking classification "with its de-centered subject, seems to eliminate, in advance, the possibility of identity, of critical self-consciousness and of intersubjectivity (cf. Habermas, 1979). Rather than making people up, actuarial practices unmake them."

Data derivatives [117]

Data derivatives are combination of vast data and learning correlations and association rules from it. This leads us not to certainties but to probabilities and yet the practical impact is that we decide our precautions based on result from these data derivatives to sustain in face of ever emerging and increasing risks. Data derivatives drives pre-emption not by predicting the future but by projecting fragments of data onto possible futures, producing a form of encoded intuition. As the associations are ephemeral, time sensitive, only correlated and do not show causation, it practically feels like calculated gambling. This is why it is termed 'derivative' of data as it is clear that data derivative emerges from the practices of speculative business like from the realms of derivatives trading and expands into other realms by proliferation of data science.

Sociology of Life Insurance [118]

Sociology of life insurance is very interesting because it seems so absurd, historically that people will accept the sacred time and event of death as a chance to earn money and security. As Kingsley says: "With life insurance, man and money, the sacred and the profane, were thrown together. Life insurance threatened the sanctity of life by pricing it. In the earlier part of the 19th century, the American public was not ready to commercialize death. Life insurance was rejected as a sacrilegious enterprise."

Life insurance was a business like any other with profit maximization as its main reason for existence. However, the profit justification seemed too base for an institution of its kind which deals with such sensitive, sacred product of death over a very long term. Given these circumstances, how did life insurance become common in our modern societies and overcame the resistance to such an initiative?

Two chief historical reasons can be sociologically deduced from analysis of historical documents and trends. The first is that life insurance responded by playing 'fire with fire'; as they were seen as un-religious by trying to commoditize death, they infact created and assert their own religious image of following core ethics and becoming missionaries of the religion of capitalism. Second reason was aggressive marketing strategy of agents selling life insurance as 'life insurance is sold and not bought'.

It is widely held that the rapid expansion of capitalism from 19th century and onwards created its own secular religion by numerous ways. It created possibility of emancipation by hard work and saving capital to accumulate capital, rituals were routines based on office timings, ethics were of hard work and repaying debts at due dates with capital as the sovereign overlord. Life insurance seized on this core change and disguised its material ambitions in spiritual garb. The company and its employees were projected as trust worthy ethical and life-long partners of the policyholders with concerns of policyholders as their foremost criteria. Life insurance was portrayed as a social good in capitalism as death will now not lead to insecurity or poverty to those affected. As Kingsley continues "Indeed, by the latter part of the 19th century, when American business felt sufficiently confident to seek no other justification than the wealth it produced, life insurance still retained part of its religious camouflage. Even some of the most hard-bitten business leaders of the industry slipped into sentimentalism in speaking of life insurance as a "conviction first and then a business" (Kingsley 1911, p. 13)."

Secondly, the distinctive and vital role of the agent in life insurance was a response to powerful client resistance. Persuasive and persistent personal solicitation alone could break through the ideological and superstitious barriers of the public against insuring life." While the companies trained the agents to market themselves to consumers as above materialistic concerns and showcase their ethics and tasks with missionary-level spiritual devotion, the highest rewards went to the successful salesman who sold the most policies.

Appendix B4- Underwriting Cycles [119]

While Property-Casualty insurance is quite competitive, it has its share of collective irrationalities and unintended consequences of actions. The winner's curse is where insurer continuously quote low premiums in a bid to gain greater market share. They then suffer heavy losses when claims start erupting and the premiums and hence reserves are inadequate to cover them.

Usually there are three tiers of insurers in the market. The first tier is the top 3 or top 5 insurers that dominate market share, are market movers and have huge underwriting scales. First tier looks to its competition mainly within its own tier like an oligopoly.

Second tier is the middle level insurers. They have stable market standings and are dynamic. They do not have the advantage of scale like first tier but they are more stable than the third tier. They focus on growth to reach the first tier and avoid regressing through losses to the third tier.

Third tier is the newly established companies, companies with low capital and market share. They usually focus on niche marketing or specialized lines but new companies also focus on gaining larger market share. They are price takers in that they use the premiums made by first tier market movers as base standard.

While insurers regard overall market movements and trends, most of comparison and strategic vigilance in a game theory type of environment is within the tiers of their market standing respectively.

Such clustered behavior can lead to herd behavior. An instance is the case of pricing wars. Excessive competition over prices to secure greater market share leads to eventual worsening of underwriting performance. Executives eventually decry this trend in publications like surveys and trade magazines as well as in conferences. This signals to the market that higher prices need to be insisted upon now. It may take only a few market makers to raise prices as they are well established and source of comparison and transparency for all of the industry. Following this, every other insurer follows suit in raising premiums.

Another sociological reason for underwriting cycles is identified by Fitzpatrick (2004) as due to the "ebb and flow of bureaucratic influence" among different departments within an insurance company. Different departments have different roles, functions and objectives. Insurance companies are ultimately composed of individuals and their judgment affects pricing decisions and this itself drives the cycles on insurance markets. Greed is promoted in times of greed and fear is adhered to in times of fear. Underwriters have the upper hand in profitable times and they push prices down to maximize sales and revenue. The more risk cautious claims adjusters and actuaries are more powerful at times when the insurer is in financial distress; they lobby to raise prices to restore profitability.

Developing further on this line of inquiry, Ingram and Underwood (2010) and Ingram et al. (2012) map these attitudes to insurance functions. Underwriters are `individualists': they are risk-taking profit maximizers. Claims adjusters are `egalitarians': they are risk-averse conservators. Actuaries are `authoritarians': they are prudent risk managers. Other operations managers (for example in IT departments) are `fatalists': they are pragmatists. According to Ingram and Underwood (2010), when profits are high, profit-maximizers (underwriters) are significant and they diminish underwriting standards to compete for customers and maximize sales (and their own remuneration). When profits fall and the firm is under pressure, conservators (claims adjusters) take over and require stricter underwriting standards. Eventually risk managers (actuaries) gain more prominence as they aid the company restore its finances. At various points, the pragmatists help out, making alliances with all parties to enable the company to keep operating. Ultimately, profitability is restored, memory vanishes and the profit maximizers take over again which repeats the cycle again.

Prospect theory is an important tenant of behavioral finance for describing our behavior. Bromiley (1991) and Fiegenbaum and Thomas (1988) describe an extension of prospect theory to the firm. They argued that a firm's aspirations serve as target or reference levels. Firms expecting returns below the relevant reference level will be risk seeking while those above will be risk averse. Palmer and Wiseman (1999) also highlight that when decision makers are faced with the prospect of failing to meet their objectives, they accept higher risk options that offer an opportunity to attain the objective and avoid the loss. In contrast, when decision makers think they will achieve their goals they will take the safer options that avoid jeopardizing the attainment of the goals. This can be seen by insurers focusing more on alternative investments in times of low interest to gain higher returns; insurers diversifying in other lines of business not previously considered when pricing wars in main lines reach unsustainable levels; insurers relaxing underwriting standards to achieve greater revenue; insurers investing more in technology and data science that disrupts traditional markets in order to create a newer market and so on [120].

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