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2036: AN ACTUARIAL ODYSSEY WITH AI

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Machines currently do what once required human expertise, including tax preparation (United States and other countries), journalism (writing articles based on events), surgery, driving cars, flying aircraft (auto-pilot) and writing software code (e.g., MS Excel macro recorder). We believe most readers would want to know whether machines (software) would someday take away actuarial jobs. In other words, will we be replaced by HAL 9001?[1] Ultimately, a lot, if not all, of what actuaries *currently* do will be taken over by machines in the future. The uncertainty involves the time frames over which the various stages in the transition would take place.

Historically, there have been key phases in interaction of technology with the professions. Starting with the so-called industrial revolution, marked by the advent and use of engines, the next phase was marked by the invention and application of electricity, and the third phase marked by the Internet/web technology explosion. Many observers see us on the verge of a fourth phase, which is an explosion in the use of artificial intelligence (AI) applications.

Many would agree that the past three phases have ultimately led to progress/prosperity for humanity as a whole. However, it remains to be seen if this fourth wave spearheaded by AI is a net positive or negative. In the short term, one thesis is that, so long as the changes are gradual, enabling adaptation by humans, the potential for negative impact will be minimal.[2] Consequently, this would suggest a cause for concern about a potential pending "AI-calypse"[3] if the rate of change is deemed too drastic. There are a number of factors that interact to determine the effects of significant use of AI in the workplace. One of the most important will be the rate of adaptation by the workforce to create value in addition to or to complement what our ever-capable machines do. This topic in the generic sense has been discussed by many authors and along different dimensions, including impact on employment levels, the related issue of resulting distribution of wealth, and ethical issues bound to arise in certain situations.[4] In this article, we consider the potential impact of this fourth wave of technology on the actuarial profession.[5]

MEET THE ROBO ACTUARY AND THE ROBO ACTUARIAL ANALYST

First, let's take a generalized view of the tasks and processes actuaries perform. Actuaries traditionally create and price products that are based on insurable risks and customer demand. This is done by taking into account demographic, economic, regulatory and other external factors. Once the sale is made and the policy is on the books, actuaries set economic and policyholder assumptions for analyzing and managing the product. An important activity is to verify that the business is meeting expectations within many different internal and external metrics and reporting results up the chain, to facilitate decision-making. Generally, the actuary's work involves activities including setting assumptions, building models, analyzing and communicating results, and developing appropriate value-enhancing strategies.

Second, we explain what we mean by the term "robo actuary."[6] A robo actuary is software that can perform the role of an actuary. Though many actuaries would agree certain tasks can and should be automated, we are talking about more than that here. We mean a software system that can more or less autonomously perform the following activities: develop products, set assumptions, build models based on product and general risk specifications, develop and recommend investment and hedging strategies, generate memos to senior management, etc.

Finally, we introduce a closely related term, "robo actuarial analyst," a system that has limited cognitive abilities but can undertake specialized activities, e.g., perform the heavy lifting in model building (once the specification/configuration is created), perform portfolio optimization, generate reports including narratives (e.g., memos) based on data analysis, etc. When it comes to introducing AI to the actuarial profession, we believe the robo actuarial analyst would constitute the first wave and the robo actuary the second wave, which we speculate are achievable in the next five to 10 years and 15 to 20 years, respectively.

WHAT IS AI? WHAT IS ITS CURRENT STATE?

Currently, AI is a buzz word used to lump together different computer science and statistics concepts. At the heart of AI is making intelligent machines that can understand their environment and react accordingly. From the 1950s when John McCarthy coined the term, it is noted in Kaplan (2015), the original goal was to discover the fundamental nature of intelligence[7]and reproduce it electronically. This goal has not been achieved (yet) but progress is being made and many believe it is achievable though the best approach to get there is not unanimously agreed upon. For this article, we will broadly classify AI systems similar to Hawkins and Dubinsky (2016),[7] as belonging to the categories of rule/knowledge-based systems, machine learning systems and "machine intelligence." The latter is based on the core mechanism for exhibiting intelligence.

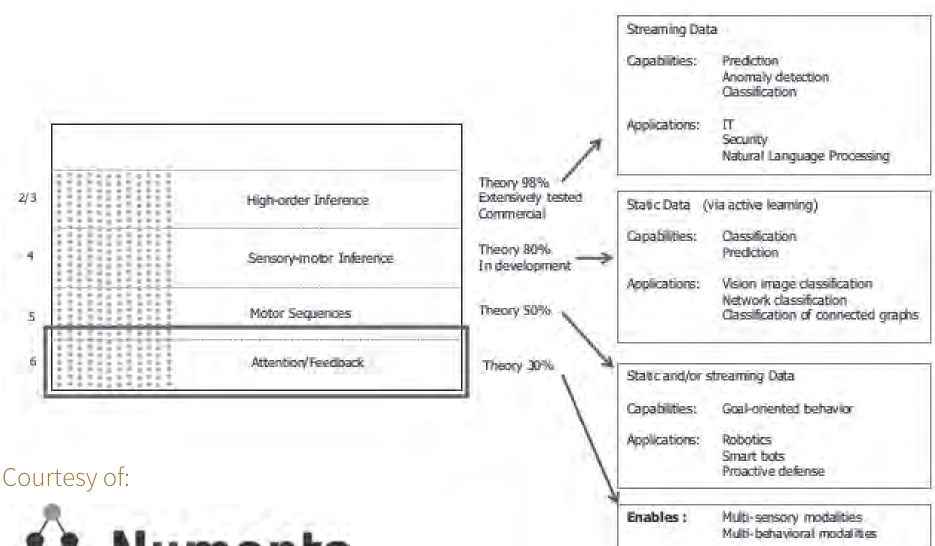
Rule/knowledge-based systems use preprogrammed algorithms and/or look up information to exhibit intelligence. IBM's Watson is a good example of this, as is RGA's AURA e-Underwriting Solution. Classic AI has solved some clearly well-defined problems but is limited by its inability to learn on its own and by the need to create specific solutions to individual problems. In this regard, in spite of it being called artificial intelligence, it has very little in common with general human intelligence.

Machine learning techniques were designed because the rule-based systems become very cumbersome and difficult to maintain/extend. This is because rule-based systems are very problem-specific and any new capabilities have to be laboriously coded and integrated with existing code. Machine learning is a mechanism to find patterns in data without requiring explicit rules. A subset of machine learning is artificial neural networks (ANN), which are based upon 1950s and 1960s understanding of how neural networks work in the brain. ANN methods have evolved into deep-learning techniques. These techniques have splintered off from the original goal of AI to develop machines with brain-like features and focus more on what "works" in a given setting. Deep learning has been able to solve many classification problems, but it needs lots of training data and it can only find static patterns. It fails at recognizing patterns that change and evolve.[8]

Machine intelligence is an approach that seeks to achieve the original goal of replicating human intelligence in electronic form. This approach would have characteristics including the adaptability to different problem domains compared to the general tailored solutions that the first two approaches entail. In that regard, the concept of hierarchical temporal memory (HTM), developed by Numenta, Inc., is probably the most popular attempt toward (true) machine intelligence. HTM is based on the latest research of the neocortex. It simulates how the brain learns in a universal and a continuous way, with robustness to noisy data inputs. One important advantage of HTM over machine learning and classic AI is that the models do not have to be trained manually and there are no tuning parameters. Just like the brain's cognitive processes, HTM is a general purpose problem-solving algorithm. This means the construction of predictive models can be automated. This is the holy grail of AI, because there are massive amounts of data and nowhere near enough data scientists to model it. Numenta has developed an open source project called Numenta Platform for Intelligent Computing (NuPIC), which can be used to develop HTM applications. The following graphic from Numenta shows the current state of the research and what has been commercially developed. The table (courtesy of Numenta) below describes the current understanding of the theory in terms of the four layers of the neocortex.

Finally, we believe many readers can wrap their minds around manual labor or repeatable office activities being taken over by machines, e.g., vacuuming or cleaning the floor, assembly of cars, generation of email alerts, etc. However, with advances in AI in general, and machine learning in particular, computers are proving capable in more and more areas hitherto thought to be limited to the domain of human cognition. For example, machines currently do things like medical diagnosis, surgery, journalism (writing of articles)[9] and driving cars. In fact, there is even a credible expectation in some quarters that artificial intelligent agents will be on major company boards by 2026![10]

Figure 1: Research Roadmap



Courtesy of:

Numenta

ROBO ACTUARIAL ANALYST AND ROBO ACTUARY WITHIN THE AI FRAMEWORK

A robo actuarial analyst is somewhat akin to an actuarial student. It would get tasks with directions from a superior in the organization and may be better/more efficient at specialized tasks than their superiors. In the shorter term, we foresee these systems interacting with human actuaries. In other words, actuaries would perform most of the higher level cognitive tasks to synthesize the lower level heavy-lifting that would then be undertaken by the robo actuarial analyst. This is similar to how one would configure a model to solve an optimization problem. The difference here is the

robo actuarial analyst would be capable of much more than we currently use software systems for. In the next section, we provide an example of how such a robo analyst can do much more than current systems as configured are able to do.

In addition, it is well known that current commercialized AI solutions are more adept/effective in solving specialized problems, e.g., surgery, speech recognition, driving, flying, than general activities like autonomously setting assumptions and making judgments and predictions in a broader-based context, relying on sometimes vague and noisy data. Longer term, machines would be able to handle higher level cognitive actuarial tasks, leading to a scenario where nonhuman systems would interact with the robo actuarial analyst in ways that only human actuaries are able to in the shorter term. This leads us to the concept of a robo actuary. A robo actuary is a system that would have higher cognitive functionality relative to a robo actuarial analyst. We note that from a software architecture perspective, robo actuary and robo actuarial analyst systems could be different components of a single system. We would refer to these systems generally as robo actuarial systems.

A HYPOTHETICAL WORK DAY FOR A ROBO ACTUARIAL ANALYST

We believe most of the heavy lifting work actuaries currently do can be effectively automated, and that is indeed happening. In addition, most of the required underlying technology and framework illustrated in this section is already available.

The robo actuarial analyst will need to be fed the right data/input to perform its processes. One way of simplifying the process for the actuary would be to create a natural language interface that would be higher level than most currently available domain specific languages (DSLs)[11] for the given area of actuarial work. For example, on a given day, a hedging robo actuarial analyst could have an email interface with which an asset-liability management (ALM) actuary could request specific analyses of current hedge positions on the books. A simulation-based analysis would be made with results summarized using both graphics and narrative. The results could be returned with appropriate documents or with links to a central repository of such documents.

Some of the key components of such a system in the light of current technology would include the ability to:

- Map natural language to a set-up/configuration of a simulation model. The building blocks (however rudimentary) of this are already in place, e.g., natural language processing (NLP) solutions including automated voice services on the phone. Taking this a step further, with an appropriate machine-learning capability added to such a system, it should be possible for a component of the system to convert narrative specifying assets/liability characteristics, assumptions and other inputs to create an "internal model representation," which would then be used by the system to generate the software code to create new asset/liability models or update existing ones.
- Run simulation of a hedge strategy. A classical AI system with simulation logic of hedge positions would suffice.
- Generate graphics and narratives from data. Arguably, the leading commercial provider of these services is the firm Narrative Science (see, for example, CITO Research 2016) and their software has been used by firms including financial and news organizations such as Credit Suisse, Nuveen Investments, USAA, CNN and Forbes.

A HYPOTHETICAL WORK DAY FOR A ROBO ACTUARY

As mentioned earlier, the robo actuary would possess higher cognitive skills compared to the robo actuarial analyst. A system that exhibits machine intelligence would possess higher levels of cognition and hence functionality, including dispatching subproblems to the more specialized robo actuarial analyst systems because it is predicated on the general purpose problem-solving capabilities of the brain.

Using the NuPIC technology, for example, any work that requires monitoring of trends and analysis of patterns is ripe for automation once neocortex layers 2/3, 4 and 5 are commercially available. Layer 2/3 is currently available but it learns from streaming data, such as market data.[12] Layer 4 is currently in development, but it only learns from slow moving or static data, such as policyholder data. Layer 5 is specialized in goal-oriented tasks, which allows for optimization of profit and capital management from the anomalies and patterns learned from layers 2/3 and 4. Once the policy data is tracked in the admin system and data is streamed from a service such as Bloomberg, the systems can encode the data into a sparse distributed representation (SDR), the data structure utilized by the brain. The SDR allows many different problems to be solved in a uniform way using the HTM algorithm of all the neocortex layers. The SDR is like a computer word with 0 and 1 bits, but, unlike the computer, each bit has a semantic meaning. Given the SDR size is large enough, on the magnitude of 10,000 bits or more, vast amounts of information can be encoded to learn complex patterns, have early detection of anomalies and potentially make goal-oriented decisions.

WILL THIS BE THE END OF THE ACTUARIAL PROFESSION?

To the question of whether AI would mean the end of the actuarial profession, we believe that is not necessarily the case. On the other hand, the profession as we know it today will most likely end.

We believe the increasing use of AI will open other avenues for actuaries. It is conceivable that regulators would still be involved with the various actuarial activities. For instance, regulators are moving away from formula-based reserves to principle-based reserves. This entails moving away from the easy generalization that formulas provided them for regulation. They are concerned with reserve and capital levels in so much as these provide signals of a viable company able to meet its promises to policyholders. HTM-based models could be employed by regulators to determine patterns of healthy companies and provide early anomaly detection to identify failing ones. The beauty of HTM is that it can recognize patterns that change and evolve based on a wide range of metrics without parameter tuning. This will allow regulators to regain the generalization they lost by switching from formula reserves to principle-based reserves. This will enable auditors to focus on more relevant details instead of irrelevant minutiae. Thus, this would present opportunities for actuaries in regulatory, or even auditing roles, to determine principles and standards of practice that are abreast with the times.

In addition, both machine learning and machine intelligence systems rely on the concept of "learning" in that they need to build a representation of the world based on their prior interaction with the world. A key component in the evolution of the robo actuarial systems would be mechanisms of training these systems. We foresee the possibility of an industry for creating solutions that will train these systems to perform their actuarial roles. The SOA and other actuarial bodies will have a part in developing mechanisms to test these systems to ensure they adhere to whatever principles are deemed to be necessary for the health of the actuarial industry and society. Recently, Microsoft launched an AI version of a "teenage girl" called Tay that was supposed to interact with humans on Twitter. From all indications, it seemed like the "training" provided the system did not impose any principles/code of communication, leading to embarrassing tweets from Tay.[13] In a sense, Tay did what it was supposed to do if that was simply to be able to learn how to interact based on tweets it received. It received a good dose of embarrassing tweets and was a quick study to emulate that line of tweeting! In a similar manner, it is possible for robo actuarial systems to learn the wrong things if not properly trained to put their activities within a framework of sorts.

CONCLUSION

In conclusion, though there is concern that machines will take over human work, we believe there is the opportunity for humans to reinvent themselves to be relevant in the light of new developments in artificial intelligence. In particular, we believe the actuarial profession is not exempt from changes due to the increasing involvement of AI in the workplace. On the bright side, with increasing sophistication and intelligence, hopefully HAL 9001 will not have a reason to dominate or even kill us! ■

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ENDNOTES

1 Readers not familiar with HAL 9001 can refer to http://www.mariowiki.com/HAL_9001.

2 The case is made in Kaplan (2015). The reason there isn't too much pain for the worker for the past few phases is the gradual nature of the change.

3 A play on AI and apocalypse.

4 See Kaplan (2015). A relatively recent fall-out from machines in finance occurred on May 6, 2010 in the stock market sell-off due to algorithmic trading platforms.

5 In Susskind and Susskind (2015), impact of AI on the professions is studied though the actuarial profession is not explicitly included. Professions such as accounting, architecture, medicine, etc., were mentioned.

6 The inspiration for the name comes from the reference to "robo (financial) advisors," e.g., see Egan (2015).

7 Rule-based systems would be equivalent to what Hawkins and Dubinsky (2016) identifies as "classic AI." Also, another common classification could be to consider rule-based and machine-learning systems as "weak AI" and machine intelligence as "strong AI."(See for example, Susskind and Susskind (2015))

8 In Hornik, Stinchcombe and White (1989), where it is shown that any deterministic function of stochastic variables can be approximated by a single-layer neural-network, for example, the author's make it clear that if the functional relationship is stochastic, the results wouldn't hold.

9 As noted in Susskind and Susskind (2015), machine written articles have appeared in reputable information sources as *Forbes*, *Time*, etc. The reader can visit Narrative Science website, *https://www.narrativescience.com/*, for more.

10 Result of a survey of attendees of the 2016 World Economic forum (See for example *http://2serpent.com/2016/01/23/predictions-at-the-2016-world-economic-forum-in-davos-switzerland/*).

11 A DSL is a language for a specific domain, e.g., SQL is a DSL for interacting with relational database systems.

12 An app that does this can be downloaded at *http://numenta.com/htm-for-stocks/.*

13 See Leetaru, Kalev (2016).

14 For example see Floyd, David (2016).