

# AI in Insurance: Hype or reality?

**March 2016** 







# The Rise of Machines



The first machine age, the Industrial Revolution, saw the automation of physical work. We live in the second machine age<sup>1</sup>, in which there is increasing augmentation and automation of manual and cognitive work.

This second machine age has seen the rise of artificial intelligence (AI), or "intelligence" that is not the result of human cogitation. It is now ubiquitous in many commercial products, from search engines to virtual assistants. AI is the result of exponential growth in computing power, memory capacity, cloud computing, distributed and parallel processing, open-source solutions, and global connectivity of both people and machines. The massive amounts and the speed at which structured and unstructured (e.g., text, audio, video, sensor) data is being generated has made a necessity of speedily processing and generating meaningful, actionable insights from it.



# Demystifying Artificial Intelligence



However, the term "artificial intelligence" is often misused. To avoid any confusion over what AI means, it's worth clarifying its scope and definition.

- AI and Machine Learning Machine learning is just one topic area or sub-field of AI. It is the science and engineering of making machines "learn." That said, intelligent machines need to do more than just learn they need to plan, act, understand, and reason.
- Machine Learning & Deep Learning

   Machine learning and deep learning
   are often used interchangeably. Deep learning is actually a type of machine learning that uses multi-layered
   neural networks to learn. There

- are other approaches to machine learning, including Bayesian learning, evolutionary learning, and symbolic learning.
- AI and Cognitive Computing –
  Cognitive computing does not have
  a clear definition. At best, it can be
  viewed as a subset of AI that focuses
  on simulating human thought process
  based on how the brain works. It is also
  viewed as a "category of technologies
  that uses natural language processing
  and machine learning to enable
  people and machines to interact more
  naturally to extend and magnify human
  expertise and cognition."<sup>2</sup> Under either
  definition, it is a subset of AI and not an
  independent area of study.
- AI and Data Science Data science<sup>3</sup> refers to the interdisciplinary field that incorporates, statistics, mathematics, computer science, and business analysis to collect, organize, analyze large amounts of data to generate actionable insights. The types of data (e.g., text, audio, video) and the analytic techniques (e.g., decision trees, neural networks) that both data science and AI use are very similar. Differences, if any, may be in their purpose. Data science aims to generate actionable insights to business, irrespective of any claims about simulating human intelligence, while the pursuit of AI may be to simulate human intelligence.

<sup>2</sup> Why cognitive systems? http://www.research.ibm.com/cognitive-computing/why-cognitive-systems. shtml#fbid=Bz-oGUiPkNe

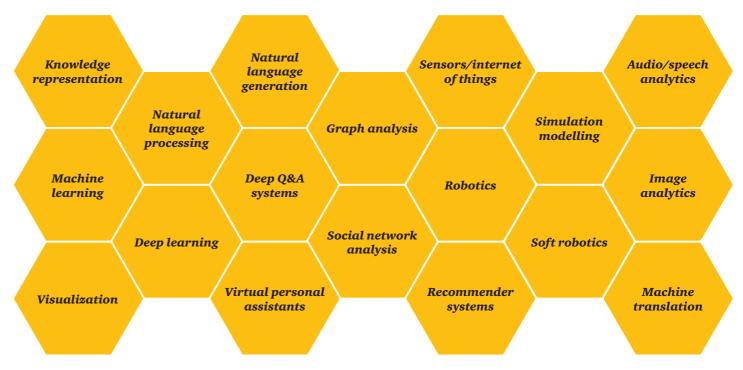
<sup>3</sup> A very short history of Data Science http://www.forbes.com/sites/gilpress/2013/05/28/a-very-short-history-of-data-science/#e91201269fd2

#### **Self-Driving Cars**

When the US Defense Advanced Research Projects Agency (DARPA) ran its 2004 Grand Challenge for automated vehicles, no car was able to complete the 150-mile challenge. In fact, the most successful entrant covered only 7.32 miles. The very next year, five vehicles completed the course. Now, every major car manufacturer is planning to have a self-driving car on the road within the next five to ten years and the Google Car has clocked more than 1.3 million autonomous miles.

AI techniques – especially machine learning and image processing, help create a real-time view of what happens around an autonomous vehicle and help it learn and act from past experience. Amazingly, most of these technologies didn't even exist ten years ago.

Figure 1: Topic areas within artficial intelligence (non-exhaustive)



As the above diagram shows, artificial intelligence is not a monolithic subject area. It comprises a number of things that all add to our notion of what it means to be "intelligent." In the pages that follow, we provide some examples of AI in the insurance industry; how it's changing the nature of the customer experience, distribution, risk management, and operations; and what may be in store in the future.



#### Personalized customer experience: Redefining value proposition

#### **Customer experience**

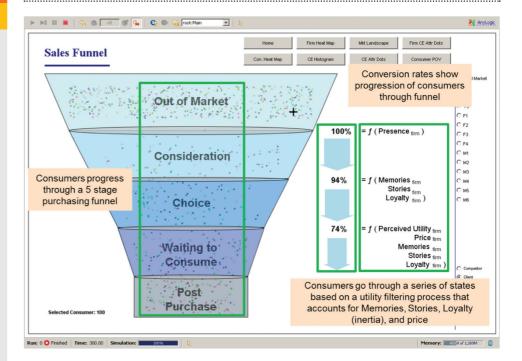
#### Early Stage: Many insurers are already in the early stages of enhancing and personalizing the customer experience. Exploiting social data to understand customer needs and understanding customer sentiments about products and processes (e.g., claims) are some early applications of Al.

- Intermediate Stage: The next stage is predicting what customers need and inferring their behaviors from what they do. Machine learning and reality mining techniques can be used to infer millions of customer behaviors.
- Advanced Stage: A more advanced stage is not only anticipating the needs and behaviors of customers, but also personalizing interactions and tailoring offers. Insurers ultimately will reach a segment of one by using agent-based modeling to understand, simulate, and tailor customer interactions and offers.

#### Al in customer experience

- Natural Language Processing:
   Use of text mining, topic modeling, and sentiment analysis of unstructured social and online/offline interaction data.
- Audio/Speech Analytics: Use of call center audio recording to understand reasons for calls and emotion of callers.
- Machine Learning: Decision tree analysis, Bayesian learning and social physics can infer behaviors from data.
- Simulation Modeling: Agent-based simulation to model each customer and their interactions.

Figure 2: PwC's Experience Navigator: Agent-based Simulation of Experience





#### Digital advice: Redefining distribution

#### Financial advice

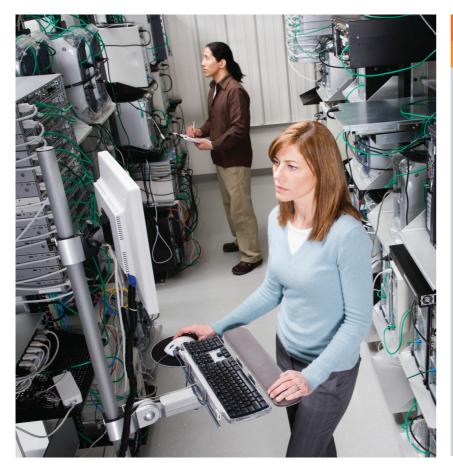
- Early Stage: Licensed agents traditionally provide protection and financial product advice. Early roboadvisors have typically offered a portfolio selection and execution engine for self-directed customers.
- Intermediate Stage: The next stage
  in robo-advisor evolution is to offer
  better intelligence on customer needs
  and goal-based planning for both
  protection and financial products.
   Recommender systems and "someone
  like you" statistical matching will
  become increasingly available to
  customers and advisors.
- Advanced Stage: Understanding
   of individual and household balance
   sheets and income statements, as well
   as economic, market and individual
   scenarios in order to recommend,
   monitor and alter financial goals and
   portfolios for customers and advisors.

#### Al in financial advice

- Natural Language Processing: Text mining, topic modeling and sentiment analysis.
- Deep QA Systems: Use of deep question answering techniques to help advisors identify the right tax advantaged products.
- Machine Learning: Decision tree analysis and Bayesian learning to develop predictive models on when customers need what product based on life-stage and life events.
- Simulation Modeling: Agent-based simulation to model the cradle-tograve life events of customers and facilitate goal-based planning.
- Virtual Personal Assistants:
   Mobile assistants that monitor the behavior, spending, and saving patterns of consumers.

Figure 3: PwC's \$ecure: Al-based Digital Wealth Management Solution





#### **Automated & augmented underwriting: Enhancing efficiencies**

#### **Underwriting**

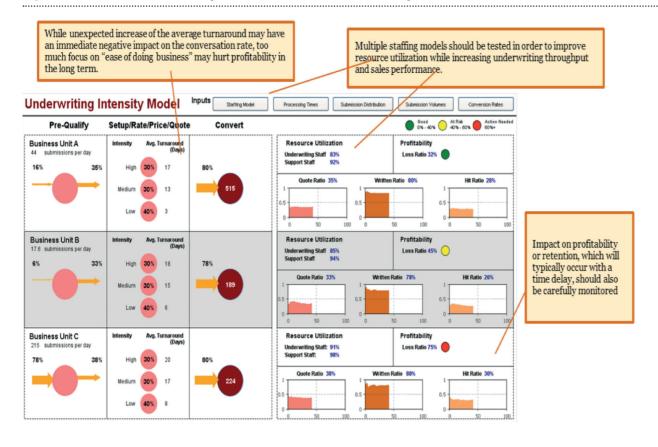
- Early Stage: Automating large classes of standardized underwriting in auto, home, commercial (small & medium business), life, and group using sensor (internet of things – IoT) data, unstructured text data (e.g., agent/advisor or physician notes), call center voice data and image data using Bayesian learning or deep learning techniques.
- Intermediate Stage: Modeling of new business and underwriting process using soft-robotics and simulation modeling to understand risk drivers and expand the classes of automated and augmented (i.e., human-performed) underwriting.
- Advanced Stage: Augmenting of large commercial underwriting and life/disability underwriting by having Al systems (based on NLP and DeepQA) highlight key considerations for human decision-makers. Personalized underwriting by company or individual takes into account unique behaviors and circumstances.

#### Al in underwriting

- Deep QA Systems: Using deep question answering techniques to help underwriters look for appropriate risk attributes.
- Soft robotics: Use of process mining techniques to automate and improve efficiencies.
- Machine Learning: Using decision tree analysis, Bayesian networks, and deep learning to develop predictive models on risk assessment.
- Sensor/Internet of Things: Using home and industrial IoT data to build operational intelligence on risk drivers that feed into machine learning techniques.
- Simulation Modeling: Building deep causal models of risk in the commercial and life product lines using system dynamics models.



Figure 4: Discrete-event modeling of new business and underwriting





#### Robo-claims adjuster: Reducing claims processing time and costs

#### **Claims**

- Early Stage: Build predictive models for expense management, high value losses, reserving, settlement, litigation, and fraudulent claims using existing historical data. Analyze claims process flows to identify bottlenecks and streamline flow leading to higher company and customer satisfaction.
- Intermediate Stage: Build robo-claims adjuster by leveraging predictive models and building deep learning models that can analyze images to estimate repair costs. In addition, use sensors and IoT to proactively monitor and prevent events, thereby reducing losses.
- Advanced Stage: Build claims insights platform that can accurately model and update frequency and severity of losses over different economic and insurance cycles (i.e., soft vs. hard markets). Carriers can apply claims insights to product design, distribution, and marketing to improve overall lifetime profitability of customers.

#### Al in claims

- Soft robotics: Use of process mining techniques to identify bottlenecks and improve efficiencies and conformance with standard claims processes.
- Graph Analysis: Use of graph or social networks to identify patterns of fraud in claims.
- Machine Learning: In order to determine repair costs, use
  of deep learning techniques to automatically categorize the
  severity of damage to vehicles involved in accidents. Use
  decision tree, SVM, and Bayesian Networks to build claims
  predictive models.
- Sensor/Internet of Things: In order to mitigate risk and reduce losses, use of home and industrial IoT data to build operational intelligence on frequency and severity of accidents.
- Simulation Modeling: Building deep causal claims models using system dynamic and agent-based techniques and linking them with products and distribution.



# Emerging risk identification through man-machine learning



"People worry that computers will get too smart and take over the world, but the real problem is that they're too stupid and they've already taken over the world."

**Pedro Domingos** author of The Master Algorithm

**Emerging Risks & New Product** Innovation – Identifying emerging risks (e.g., cyber, climate, nanotechnology), analyzing observable trends, determining if there is an appropriate insurance market for these risks, and developing new coverage products in response historically have been creative human endeavors. However, collecting, organizing, cleansing, synthesizing, and even generating insights from large volumes of structured and unstructured data are now typically machine learning tasks. In the medium term, combining human and machine insights offers insurers complementary, value generating capabilities.

Man-Machine Learning – Artificial general intelligence (AGI) that can perform any task that a human can is still a long way off. In the meantime, combining human creativity with mechanical analysis and synthesis of

large volumes of data – in other words, man-machine learning (MML) – can yield immediate results.

For example, in MML, the machine learning component sifts through daily news from a variety of sources to identify trends and potentially significant signals. The human learning component provides reinforcement and feedback to the ML component, which then refines its sources and weights to offer broader and deeper content. Using this type of MML, risk experts (also using ML) can identify emerging risks and monitor their significance and growth. MML can further help insurers to identify potential customers, understand key features, tailor offers, and incorporate feedback to refine new product introduction. (N.B.: Combining machine learning and agentbased modeling will enable these MML solutions.)

#### Computers that "see"

In 2009, Fei-Fei Li and other AI scientists at Stanford AI Laboratory created ImageNet, a database of more than 15 million digital images, and launched the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). The ILSVRC awards substantial prizes to the best object detection and object localization algorithms.

The competition has made major contributions to the development of "deep learning" systems, multilayered neural networks that 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.



# Artificial intelligence: Implications for insurers



AI's initial impact primarily relates to improving efficiencies and automating existing customer-facing, underwriting and claims processes. Over time, its impact will be more profound; it will identify, assess, and underwrite emerging risks and identify new revenue sources.

- Improving Efficiencies AI is already improving efficiencies in customer interaction and conversion ratios, reducing quote-to-bind and FNOL-to-claim resolution times, and increasing new product speed-to-market. These efficiencies are the result of AI techniques speeding up decision-making (e.g., automating underwriting, auto-adjudicating claims, automating financial advice, etc.).
- Improving Effectiveness Because of the increasing sophistication of its decision-making capabilities, AI soon will improve target prospects in order to convert them to customers, refine risk assessment and risk-based pricing, enhance claims adjustment, and more.

- Over time, as AI systems learn from their interactions with the environment and with their human masters, they are likely to become more effective than humans and replace them.

  Advisors, underwriters, call center representatives, and claims adjusters likely will be most at risk.
- Improving Risk Selection &
   Assessment Al's most profound
   impact could well result from its
   ability to identify trends and emerging
   risks, and assess risks for individuals,
   corporations, and lines of business.
   Its ability to help carriers develop new
   sources of revenue from risk and
   non-risk based information also will
   be significant.



## Starting the Journey



Most organizations already have a big data & analytics or data science group. (We have addressed elsewhere<sup>3</sup> how organizations can create and manage these groups.) The following are specific steps for incorporating AI techniques within a broader data science group.

1. Start from business decisions –
Catalogue the key strategic decisions that
affect the business and the related metrics
that need improvement (e.g., better
customer targeting to increase conversion
ratio, reducing claims processing time
to improve satisfaction, etc.).

- 2. Identify appropriate AI areas Solving any particular business problem very likely will involve more than one AI area. Ensure that you map all appropriate AI areas (e.g., NLP, machine learning, image analytics) to the problem you want to address.
- 3. Think big, start small AI's potential to influence decision making is huge, but companies will need to build the right data, techniques, skills, and executive decision-making to exploit it. Have an evolutionary path towards more advanced capabilities. AI's full power will become available when the AI platform continuously learns from both the environment and people (what we call the "dynamic insights platform").
- 4. Build training data sets Create your own proprietary data set for training staff and measuring the accuracy of your algorithms. For example, create your own proprietary database of "crash images" and benchmark the accuracy of your existing algorithms against them. You should consistently aim to improve the accuracy of the algorithms against comparable human decisions.
- 5. Pilot with Parallel Runs Build a pilot of your AI solution using existing vendor solutions or open source tools. Conduct parallel runs of the AI solution with human decision makers. Compare and iteratively improve the performance/accuracy of AI solution.
- 6. Scale & Manage Change Once the AI solution has proven itself, scale it with the appropriate software/hardware architecture, and institute a broad change management program to change the internal decision-making mindset.



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