Welcome to the first issue of *Predictions*, a supplement and dedicated microsite (URL tbc) produced by *The Actuary* magazine, and sponsored by Willis Towers Watson, exploring the challenges and new opportunities technology presents for the financial sector and the actuarial profession.

Technology is transforming existing business models and creating brand new ones, and in doing so changing the way we live our lives in many respects. It is making it easier for customers to access information and services, and helping markets operate more efficiently by creating new ways to manage supply and demand. The most successful examples of disruptive technologies are those that give the customer more control and put them at the centre of what the business does.

In this issue we look at the potential for technology to disrupt the financial world, one that has so far seen relatively little transformation through new technology. We look at how Robo-advice is already widening access to financial advice for many customers, while Blockchain could transform the way insurers manage claims, and eventually turn them in to risk prevention specialists.

We also ask how actuaries can respond to the emergence of new technologies by utilising new data sources, such as telematics, to prepare for the dawn of driverless cars. Meanwhile we consider how new data science techniques can help actuaries maintain a competitive edge.

Finally, we look at how firms can respond by creating a more ‘customer centric’ business model. The microsite offers an exclusive article, *A state of mind, not just a slogan* by Willis Towers Watson, looking at what insurers can do to adapt and put the consumer at the heart of their business, so that customer centricity becomes more than just a snappy slogan.
Blockchain technology is viewed with interest by governments and financial markets. Some believe it could hold considerable disruptive powers. Gary Nuttall provides an overview and separates the hype from the reality.

The global banking sector is estimated to have invested over $1bn in blockchain technology in the last 12-18 months. In 2015 alone, it is estimated that bitcoin and blockchain start-ups raised nearly $500m in funding.

In January this year, the UK government’s chief scientific officer published a report that suggested the technology would be game-changing and would provide great opportunities for companies to develop solutions. The report also suggested a variety of potential uses for the technology, including the delivery of government services.

‘Blockchain technology’ is a term that is often used interchangeably with ‘mutual distributed ledger’, although, arguably, this is incorrect:

● A ledger is a record of transactions
● A mutual ledger is a ledger to which all participants have access
● A mutual distributed ledger is, as the name suggests, a mutual ledger that has been distributed, such that everybody involved has a complete, synchronised copy
● When the data is stored as a series of sequential blocks, each of which is cryptographically chained to the previous block, this is called a ‘blockchain’.

To keep it simple, the term blockchain can be used to describe a mutual distributed ledger database that everyone has an identical copy of, and that is cryptographically secured and time-stamped.

Why the excitement?
Blockchain is sometimes described as being ‘the next internet’ and could be a highly disruptive technology, due to a number of key features:

Transfer of value without a trusted intermediary
If you wish to participate in a financial transaction, you need to use a trusted third party, such as a bank or credit card provider (unless you’re paying in cash).

With blockchain you can simply reassign the ownership of value directly, since everything is held in a single ledger. This could dramatically impact industries that have been created due to lack of trust between counterparties, for example, conveyancing, banking and escrow agents. The digital currency, bitcoin, is an example of the use of blockchain for value transfer.

Smart contracts
This is perhaps a poor choice of words since so-called ‘smart contracts’ are neither smart, nor contracts in the legal sense. A smart contract is self-executing computer code that runs on the blockchain. Smart contracts allow the ability to link external events identified through an external data supply such as weather reports, flight delays and shipping manifests. To be able to code that automatically presents significant opportunities to develop new products and services.

The DAO, which stands for decentralised autonomous organisation, is a well-known example of using smart contracts to create an entire, self-managing eco-system. It raised in excess of $150m through crowdfunding. However, it may turn out to be a classic example of adapting technology before sufficient maturity has been achieved; as over $50m was quickly siphoned off by a hacker who exploited a design feature.
“Blockchain is sometimes described as being ‘the next internet’ and could be a highly disruptive technology”

Immutability
As each block of data is added, an algorithm, known as a cryptographic hash, is run. This produces a unique value based on the content of the block of data. This hash is then stored at the beginning of the next block and therefore forms part of the calculation of the next block’s hash. The end result is that data held in prior committed blocks cannot be amended since this would then affect the hash value of the block. This would then require the algorithm to be recalculated for each subsequent block. As such, this makes it impossible to amend data once it has been written to the ledger.

Cyber-resistant
Every participant ‘node’ in a blockchain distribution holds a complete copy of the synchronised ledger. This means that even if multiple nodes are successfully attacked then the blockchain is still able to operate. This removes the risk of distributed denial of service (DDoS) attacks and of data being subject to ‘ransomware’ attacks.

Crypto-secure
Using a combination of public and private cryptographic keys, it is possible to tightly manage and control access, such that participants can only see the data that is relevant to them.

Synchronised mutual ledger
Many organisations spend significant amounts of money on the reconciliation processes needed to check that data copied from one organisation’s ledger to another is consistent. If there is just one ledger, there is no data being transferred and therefore no need to reconcile. Likewise, auditing overheads are reduced since there are fewer processes to audit.

Applications
Blockchain has a wide range of potential applications including identity management and asset registration. For insurance, blockchain provides opportunities in two main realms. First, it allows insurers to develop new products. Linking it with other emerging technologies such as ‘internet of things’ sensors and artificial intelligence, the potential exists to develop new parametric products that can link the automatic detection of an event to the automatic payment of a claim. In the longer-term, linking these technologies together will allow insurers to become ensurers, whereby they will be able to identify that an event is going to happen and execute a preventative action. This is akin to sending an engineer to repair a faulty bearing on a machine before it fails.

Second, it provides significant savings in operational efficiency by decreasing the time, cost and effort expended on reconciling multiple ledgers. This will reduce the burden of audit by reducing the number of processes that require auditing, and by providing more reliable, provably immutable ledgers.

Hype or reality?
The concept of ledgers, mutual ledgers, distributed databases and linking blocks of data isn’t new. Indeed, back in 2008 a white paper on the bitcoin protocol was published by an anonymous author known only as Satoshi Nakamoto. Bitcoin has seen good and bad periods; it has been linked in the past with ‘dark web’ markets, such as Silk Road, which was shut down by the FBI because of the illegal trade being facilitated therein. However, the fact that bitcoin is still around today shows how robust the protocol is. Blockchain uses open source code, and with a market cap (at the time of writing) of over $10bn, it would normally present a lucrative target for hackers. To date, although other exchanges have been subject to fraud, the bitcoin blockchain itself has remained unhacked and blockchain-based technology is now well-established.

As with any emerging development, the technology presents its own challenges. In particular, performance, scalability and power consumption are known issues that are being worked on. The original bitcoin blockchain processes transactions at around 10 per minute, which makes it unsuitable for real-time financial transactions. However, new blockchains are being developed that enable throughput of over one billion transactions per day.

Currently, and this is an area moving at a great pace, there are few examples of commercial implementations at an industrial scale. However, a number of companies will soon be moving from research and development into production. Far from being just hype, therefore, blockchain is about to become a reality.

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The last two years have seen a period of profound business transformation. The human race is witnessing the rise of a robotic workforce, artificial intelligence and the internet of things. Moreover, big data analytics offers deep business insights, while cognitive computing is evolving rapidly. Even blockchain cryptography, still in its infancy, is already under threat from quantum computing.

Financial innovation, technology advances and changes in individuals’ behaviour all enforce industry change. But, most of all, financial regulation has affected the competitive landscape, and made such a transformation not only possible, but a business imperative. Regulation is the main engine for transformation, and due to the loss of reputation suffered by traditional players during the global financial crisis, fiduciary standards have been stepped up across the globe. Transparency and suitability principles have also been strengthened in order to realign the incentives of financial institutions with the ultimate interests of the taxable investor.

Technology innovation has allowed fintechs (financial technology start-up companies) to find solutions that are fit for purpose and can lower the ever-rising compliance burden. Digital business models can replace established customers’ networks and enable fintechs to reach out to investors any time, any place, with compelling, convenient and engaging investment experiences. There is no doubt banking is going digital – because today’s world is already digital.

However, technology cannot be the only answer as work is required on both sides of the equation: FINance and TECHnology. Financial innovation is needed to help investors and move them outside the traditional investment pattern of buying high and selling low. This is very often based on a myopic trading strategy of buy and sell decisions that is overly reactive to news events, rather than listening for long-term trends.

Robo-advisors – replacing face-to-face investment and savings advice with automated online guidance – possess three appealing features. First, they invite individuals to invest into portfolios supposedly geared toward longer-term performance; second, they offer cheaper investment products, such as exchange-traded funds; and finally, passive investment strategies are preferred, in order to simplify reporting and reduce management costs.

This technology has several aims: to insulate investors’ decisions (let’s be clear, not investment performance) from short-term market swings; shield investors from idiosyncratic risks; grant them longer term performance by saving on potentially excessive management fees; and, finally compound the proceeds alongside procedures of tax loss harvesting.

Wealth management institutions have already started to adopt these new business models, due to depleted balance sheets, rising compliance costs and highly unbalanced cost-to-income ratios. New ventures compete in this space, as well as established players that provide automated investment solutions alongside more traditional businesses.

Yet is this enough to make financial wealth management more sound and transparent? Quite a few elements of concern remain and need to be addressed by regulators and industry participants.

First, most robo-advisors have adopted rudimentary goal-based investment principles: they on-board clients by inviting them to invest according to personalised needs, such as retirement or school education. Figure 1 shows a timeline example of life events, wealth accumulation goals and wealth consumption requirements. Although notable, this is more thematics than goals as individuals’ assets and liabilities do not truly enter into the investment equation. Hence, only the evolution into more holistic approaches would allow for effective personalisation of the investment experience.

This limitation could be solved by techniques such as probabilistic scenario optimisation. This method avoids the limitations of modern portfolio theory and instead offers long-term portfolio construction and simulation based on real products. Such techniques can be capable of encompassing fixed income and derivatives and be adequate to resolve problems linked to cumulation and de-cumulation patterns such as pre-, at- and post-retirement decision-making.

A further challenge comes from on-boarding...
questionnaires that are way too rudimentary and do not allow digital advisors and their final investors to engage in enriching and empowering conversations. In this regard, gamification – the application of game design and principles – is emerging as a new digital force in the wealth management ecosystem. It allows for experiences to be created that help advisors and individuals make better decisions when confronted with financial news and market swings. In this respect, goal-based investment can provide gamification with the consistent mindset to gamify investments by simulating personal goals, market scenarios, and life events within a digital playground to enforce more adequate investment behaviour.

However, this development will not be free from cost. It requires a change of perspective: from a traditional asset management view of market variable optimisation, to a more personalised investment modality of eliciting investors’ ambitions and fears over time. In such a transforming environment, investors’ fears and long-term aspirations would take centre stage, and goal-based investment principles will allow financial advice and financial planning to converge. The investment offering could then be customised around clients’ ultimate goals, which would in turn generate premium services, driving profitability and sustaining innovation.

Financial innovation is paramount at a time when financial advice and financial planning are converging. While financial advice is undergoing a process of strong commoditisation, financial planning still grants more space to leverage technology and add value to the human relationship between planners and investors. All aspects of personal wealth today are linked to financial markets, meaning that long-term insurance and investment planning must adopt many aspects of financial advisory solutions.

The need for better retirement advice and planning seems to be gaining momentum: the largest cohort of baby boomers is about to retire, life expectancy has never been longer, and the workforce is shrinking at a time when modern economies struggle to generate enough growth to keep the pension challenge under control. A mix of financial and digital innovation is therefore required to facilitate the giving of robo-advice on a massive scale, so that individuals better understand the implications of investing and saving for distant goals.

This is the reason why goal-based investment robo-winners will be well-positioned to outpace laggards, whether they be fintechs or digital incumbents.

**Figure 1** An example timeline for life events

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**Fintech Innovation: from Robo-Advisors to Goal Based Investing and Gamification by Paolo Sironi is published by Wiley (2016)**

Paolo Sironi is a Thought Leader at IBM
An ever-increasing supply of data, and powerful modern computers that are able to exploit and analyse it, has led to the growth of the data science field. At its core is the concept of gaining insight from data, be it big or small. Data science techniques are employed in a wide variety of industries, from fashion retail to hedge funds.

We use the term ‘big data’ to refer to large collections of data, potentially from diverse sources, that is often unstructured, relying on text, pictures, or geographical positions, rather than fixed fields as found in more traditional data sets. But data science is not just about big data. Having big data may well require the use of machine learning technology to extract useful information; however, a lack of big data does not preclude the use of machine learning algorithms.

Machine learning

‘Machine learning’ is the process by which a computer learns by being exposed to data, generally by using an algorithm that optimises some mathematical function of that data. Once the domain of computer scientists in large research organisations, machine learning is now available to everyone through free, open-source toolboxes provided for programming languages such as R and Python. These languages have a comparatively easy learning curve and come with many functions that are built in or available to download, enabling the user to perform sophisticated tasks with ease. This functionality is invaluable to actuaries as it means the exercise is more one of data manipulation and analysis of the output than computer programming. With courses available that provide the fundamentals needed to explore the field, data science has never been so accessible to actuaries.

There are two fundamental categories of machine learning. ‘Supervised’ learning algorithms are in the business of prediction, while ‘unsupervised’ learning focuses on understanding the structure behind a data set.

Imagine trying to categorise pictures of cats and dogs. Starting from a database of such photos, each labelled either ‘cat’ or ‘dog’, supervised learning involves the creation of a predictive model that exploits the information contained in the labels. The model will make predictions by taking an unlabelled, previously unseen pet photo and deciding whether it is a picture of a cat or a dog.

Unsupervised learning takes a different approach. Running an unsupervised algorithm on a set of unlabelled photos returns a grouping of photos that are most similar. That grouping might be a separation into pictures of cats and dogs, but equally could be a separation by pet size or colour. The exact results will be determined by the parameters governing the algorithm. Although the unsupervised learning algorithm may not be able to predict pet species, this is not a failing of the algorithm since it was not supplied with the information contained in the labels. A successful unsupervised algorithm will provide information about the relationships between the pictures. It is then up to the user to interpret the information appropriately – after all, pet species is not the only information in the pictures, and for some uses, maybe pet size is more important.

Actuarial applications

Figure 1 shows some machine-learning algorithms. One such algorithm, a generalised linear model (GLM), has been used by actuaries in personal lines pricing for years. GLMs can be thought of as prototypical supervised learning algorithms. Given a set of prior claim frequencies and severities, a GLM algorithm creates a model that predicts, for a new policy, how likely it is that a claim will occur and how much it will cost. With modern computing power, these methods can be taken further with the use of algorithms, such as decision forests or neural networks. The flexibility of these algorithms allows the fitting of non-linear trends, without having to make manual assumptions. Such techniques also have the ability to identify interactions between data items that are not seen by the human eye or through the use of linear models. These ‘hidden’ interactions can then potentially be used to predict claims more effectively, leading to more competitive pricing.

While GLMs are often used to price personal lines, specialty lines in the London Market rely on the
expertise of underwriters. Marine pricing is one such example where there is a wealth of data, in this case on ship position and weather records. This is big data, which lacks clear structure and so can be difficult to analyse. However, supervised learning algorithms such as neural networks could extract features predictive of claim patterns. The information could add an extra dimension for underwriters and may offer a competitive advantage.

There are also many potential applications for unsupervised learning techniques. Unsupervised algorithms can augment and replace human-labour intensive data sorting and visualisation, particularly when the number of data fields is large. For example, grouping accounts by prior loss ratio performance, enabling quick identification of common trends or dependencies, may offer management teams a valuable insight into the company.

Beyond the black box
A common criticism levelled at machine learning is that the resulting models are too ‘black box’ like. Although a simple linear model is straightforward to understand and communicate, it is not very flexible when dealing with general data that may involve non-linear relationships. In contrast, very flexible supervised learning algorithms, such as decision forests or neural networks, can fit to quite general data patterns but at the cost of a less transparent model (see figure 2). While it might be true that the models can be complicated, the resulting model can usually be communicated sufficiently clearly by plotting the model predictions against the various predictive features. Furthermore, a variety of statistical techniques exist that can provide the user with the comfort that the model is robust and appropriate.

Data science is not a new field. It contains a multitude of tried and tested algorithms that have already been proven to be beneficial in other industries. With the development of technology giving the everyday user the computing power to use these processes, and with the tools to use these methods being easily accessible, actuaries can now apply techniques that were once only available to data specialists. In today’s competitive environment, data science could be used to supplement the tools that actuaries already have at their disposal and provide companies with that all-important edge.

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**Figure 1** Some common machine-learning algorithms

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**Figure 2** Trade-off between flexibility of algorithm and transparency of resulting model
MACHINE LEARNING

TOWARDS MACHINE PRICING
ack in 2009, I completed a research project for the actuarial profession on the applications of machine learning and more generally of artificial intelligence (AI) to general insurance. A brief summary of that work appeared on this magazine in March 2011 under the title *From artificial fish to underwriters*. Since then, I am happy to report that the ‘actuary of the future’ space on this magazine still features human beings and not androids. Everything else that could have happened in relation to automation, however, has started happening:

a) Machine learning has become a household name among actuaries (and almost everyone else), and techniques such as the lasso or elastic net regression are not esoteric names anymore.

b) The notion of big data has come to the fore and its use is the main reason why machine learning has become much more efficient, for example in speech recognition.

c) The use of new business models based on digital technology and big data (‘InsurTech’) promises to disrupt the insurance industry.

d) Deep learning (a machine learning technique based on many-layered artificial neural networks) has achieved superhuman ability in a variety of domain-specific tasks, from face recognition to the identification of tumours from radiological images, and is now regularly applied to insurance problems such as fraud recognition.

It really looks like, after so many ‘AI winters’ – those periods in history where funding for AI dried up in the wake of crushed expectations – we are going to have a spring that none of us can afford to dismiss.

**Machine learning as a theory of modelling**

The main contention of that research project – and one that has not dated – was that machine learning is not just another powerful technique that actuaries should learn. Rather, it is the only rigorous theory available on how to build models with predictive powers, whether in data-rich situations (personal lines pricing) or in sparse-data situations (London Market). The problem of data-driven risk costing (the basis of much pricing, reserving and capital modelling) is an example of supervised learning – the problem of learning the features of a model based on a sample of inputs (for example, rating factors, or the parameters in a severity model) and outputs (for example claims amount), with the objective of minimising the expected prediction error.

Therefore, actuaries should learn machine learning not only to be hip and to be well-equipped for the onslaught of big data – but because it brings clarity of thought and the right attitude to how they go about their daily job (for example, building and calibrating pricing models and deciding when to use benchmarks). Machine learning will give you mechanisms on how to optimise the complexity of your models, resisting the push towards more complicated and supposedly more ‘realistic’ models (see Figure 1, describing the famous bias-variance tradeoff).

**A pathway to automation**

As intellectually satisfying as this is, the prize for the adopters of machine learning and artificial intelligence in pricing is not purely theoretical – insurers’ CEOs are not (always) interested in theories of modelling. Also, while AI may provide valuable tools for fraud detection and data mining, the competitive advantage of using slightly more accurate costing is likely to be limited. The big prize is that machine learning provides a pathway towards pricing (and reserving, and capital modelling) automation.

The simplest and best-known example is possibly that of rating factors selection. This has never been anything but a machine learning problem. The industry standard – generalised linear modelling augmented with a mechanism to select the right...
factors – is in itself a well-known supervised learning technique. A low-hanging fruit for machine learning – well underway – is enhancing the existing industry standard with techniques such as lasso regression and cross-validation as a means to select the model with a minimum expected prediction error in a fully automated and efficient fashion. So much is available off the shelf (elastic net, kernel methods, support vector machines...) to keep us busy for years. It may well be that the distinction between all these methodologies will soon become as tedious as the distinction between different goodness-of-fit metrics.

A less obvious candidate for automation and machine learning applications is individual contract pricing in commercial lines (or treaty reinsurance). The standard process for this is a patchwork of tasks that are completely algorithmic (for example a Monte Carlo simulation to produce an aggregate loss distribution) and tasks where judgment is required (data checking and preparation, picking suitable frequency/severity models). A possible pathway towards automation is to re-engineer the process so those areas that require judgment are isolated, and a clear protocol to deal with these areas using available AI techniques is developed. A couple of examples:

- Data exploration and preparation can benefit from the use of rule-based systems (rudimentary decision systems based on simple fixed rules), natural language processing (an umbrella term for various statistical machine learning algorithms aimed at extracting information from text) and data mining.
- AI provides the natural conceptual framework for automating the selection of frequency/severity models and deciding when to resort to portfolio/market data. Where data is scarce, model selection cannot be purely data-driven, but the selection must also be informed by theoretical results (for example, using extreme value theory for large losses).

Of course, full automation would not happen in one go, but in an iterative and piecemeal fashion, as is the case for driverless cars.

**The advantages of machine pricing**

The advantages of pricing automation would be similar to automation in other fields, but with some specific twists.

1. **Machines increase the number of actuarial investigations** that can be performed. Since they don’t get tired, they can price as many deals as we want, to the desired level of detail, without needing to prioritise important work and they don’t become intractable if they receive updated information one day before the deadline.

2. Machines can **improve portfolio management** greatly. Background bots (pieces of software that perform tasks on behalf of a user) can maintain the claims database and the portfolio data, update pricing models and portfolio benchmarks (including exposure curves) continually. They can ensure that the benchmark curves maintain their relevance, rather than sticking to the same exposure curves as people used in the 60s because it would be too onerous to embark on regular reviews. They can ensure that the optimal number of different benchmark curves is used, as more claims experience accumulates and it becomes possible to differentiate risks more and more.

3. **Machines would be able to price contracts neutrally,** without a cognitive bias. Neutrality is important – human underwriters and pricing actuaries may be able to incorporate special knowledge and wisdom in specific transactions but they will not be able to guarantee unbiasedness at a portfolio level. A pricing machine may price incorrectly but will be even-handed – and its neutrality at portfolio level can also be checked and monitored by A vs E analysis. The underwriters or other officers will still have the opportunity to override the machine price but this will be documented and the portfolio effects of underwriting adjustments can be isolated and monitored.

**Yes, but what about actuarial judgment?**

Automation makes everything more efficient where it can be applied, but surely we still need sound actuarial judgement. Or do we?

It can be argued that at the basis of judgment are experience and the knowledge of the answer to many similar cases looked at in the past, that type of ‘hunch’ that immediately tells you that a particular price or parameter is a bit off. A few things can be said about this type of judgment:

a) If defined as above, judgment is ominously similar to deep learning – you train an artificial neural network on a number of relevant cases and this comes up with a strategy, which can’t be articulated but gives good results;
Specific tasks will increasingly be automated – as has been the case for decades – but this will redefine actuarial jobs rather than wipe them out

b) This type of supposedly exclusively human judgment has been invoked several times in history – most famously to explain why chess software could not possibly beat the very best humans at the game, because humans would have an intuition about positions while a machine could only look ahead a number of moves. Over and over again, however, machines have proved themselves to be better at judgment in domain-specific contexts;

c) This judgment is not always correct, especially where past experience is not that large – that will be true for both human and AI judgment.

So is the end nigh for actuaries?
If AI is so great that it may eventually replace judgment, will our jobs still be there in 20 years (the canonical timeframe for safe prediction)?

Some of the recent anxiety about jobs can be traced back to the oft-quoted paper by Frey and Osborne (2013), The future of employment: how susceptible are jobs to computerisation?, which estimates the probability of various jobs to be replaced by machines. The paper found that 47% of jobs were at high risk (60% or more) of computerisation, and put that probability for insurance underwriters at a staggering 99%. Although this datum can be put to good use for actuary vs underwriter bantering, it probably says more about the limitations of the paper’s methodology and assumptions than it does about the underwriters themselves. Specifically, the methodology fails to capture the heterogeneity of tasks performed in a specific occupation, only some of which can be automated. A subsequent study (Arntz et al. (2016), The risk of automation for jobs in OECD countries) has refined the approach and put the percentage of jobs at high risk of computerisation at a more modest 9%. Nothing specifically was mentioned about underwriters (or any other jobs) but by using their task-based approach it is clear that only a small part of an underwriter’s tasks would be amenable to automation, while most could not. The situation is not dissimilar for pricing actuaries.

Specific tasks will increasingly be automated – as has been the case for decades – but this will redefine actuarial jobs rather than wipe them out. The ‘lump of labour fallacy’ – that is, the idea that there is a finite amount of work to go around and automating it will reduce the need for people – applies to actuaries as well as to the labour market in general. The advent of desktop computers, spreadsheets, and programming languages hasn’t reduced the need for actuaries, but has increased dramatically the number of things that actuaries are asked to look at. This trend is likely to continue: AI techniques will make it cheaper to run actuarial investigations and therefore the demand for them is likely to increase. The actuary is in a privileged position to create and harness the technology and piece everything together.

All this unless, of course, automation becomes so good that it can do the harnessing, the piecing-together and even the theory-building that professionals do. This, however, is far-fetched. Replacing actuaries altogether is an AI-complete problem – that is, a problem equivalent to creating general intelligence. Despite some concerns that a hostile AI may soon take over the world, we’re not remotely close to the creation of a general intelligence that has consciousness and willpower and the pathway towards it is unclear.

I may not have the best track record for making predictions on artificial intelligence, though. When I was working at the University of Toronto I used to shake my head in disapproval on seeing my fellow post-docs wasting their best years in Geoff Hinton’s artificial neural networks lab. I, for one, was engaged in much more serious and promising theoretical research on the computational complexity of certain tasks in machine vision, building up on my PhD work. Fast forward a couple of decades: Geoff Hinton is now head of AI at Google. My PhD supervisor has long had enough of this whole machine vision business and has gone back to neuroscience. As for myself... well, I’ve become a pricing actuary, so I can’t complain at all, can I?

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Rutger van der Wall examines how telematics technology can be used to understand the risks of driverless cars.

Wether it’s motorists’ fears or fantasies about driverless cars, barely a day goes by without fresh opinion appearing in the media on the whys and wherefores of autonomous vehicles. This has recently been brought into sharper focus as the UK government has confirmed it is looking to amend the Road Traffic Act 1988 motor insurance provisions to extend mandatory motor insurance to include product liability. In a speech to insurers earlier this year, the road transport minister warned that traditional data sources for rating insurance will become obsolete with the emergence of the connected car.

If there was ever a sharp elbow prod to the insurance sector to prepare, this was it. That is not to suggest insurers have been slow to the party, far from it. They have been acutely conscious of the liability questions and involved in discussions from the outset. However, there is an urgent need to get down to the nitty-gritty and start appreciating the value that driving behaviour data, such as speeding, braking and road familiarity, will bring in understanding liability and risk and enabling cover to be provided for driverless cars.

We know that fully autonomous vehicles are not going to appear overnight – it is more realistic to consider this as a staged process. IHS Automotive, a provider of global market, industry and technical expertise, predicts that almost 76 million vehicles with some level of autonomy will be sold globally between now and 2035. This means we will see
“We have a window of opportunity to use telematics during this testing period to better understand the risks involved”

We have a window of opportunity to use telematics during this testing period to better understand the risks involved. The data collected through telematics will be invaluable for underwriters and actuaries to determine their claims loss ratios, and also how the risk changes across the different levels of autonomy.

It will also enable insurers and manufacturers to identify, in the case of an accident, whether the technology installed worked in the way expected, and also the role that human intervention played, if any. These results can then be delivered back to the insurer for them to make a judgment on the fault of the claim and who is responsible.

Fundamentally, driving data, regardless of how it is collected – whether hard wired black box, a 12V plug-in device into the cigarette lighter in the car or a driverless car – needs filtering, normalising and enriching to bring value. This is where insurers need to be focusing their time right now, to fully understand the processes and possibilities. Ultimately, this will help them meet the new legal requirements by the time fully autonomous vehicles reach UK roads.

In order to accelerate the learnings during this period, the industry needs to consider how it can work together for the benefit of all parties. For example, a data hub could be created, which would enable all insurers and OEMs to share data and learnings. Insurers could then pitch for the data sets they require. This exchange of data would provide actuaries and underwriters with access to a large amount of quality data in order to calculate risks accurately and identify emerging trends.

Insurers are already effective at sharing data with central government databases, controlling personal data to eliminate fraud, and using contributory services. So this is a good model to use in the case of driverless cars. Therefore, by working together as an industry, propositions and solutions can be created to improve the success of driverless cars with all the societal benefits this mode of transport will offer.

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