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"To be, or not to be" … an Actuary

By Dave Snell

Page 8

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To join the section, SOA members and non-members can locate a membership form on the Predictive Analytics and Futurism Section webpage at *http://www.soa.org/predictive-analytics-and-futurism/*.

Publication Schedule

Publication Month: December 2018
Articles Due: Sept. 12, 2018

From the Editor: PAF—Much More Than a One-trick Pony

By Dave Snell

My Merriam-Webster dictionary defines a one-trick pony as "one that is skilled in only one area; also one that has success only once." Occasionally, I hear a disparaging comment from a colleague that some actuaries are a one-trick pony. Sure, we math dweebs have had a lot of success in insurance risk management; but how does that help the world beyond shareholders of those companies?

In the past that would incite me to launch into the importance of various types of insurance to protect families and loved ones. I could talk or write passionately about those for a long time. As a member of the Predictive Analytics and Futurism (PAF) section though, I can add how actuaries are using their new PA skills to benefit current and future generations of humankind in other ways. Predictive analytics techniques, sometimes coupled with data from health and life insurance companies, are enabling precision medicine. This is not just insuring lives, but also improving quality of life for insureds and for the population in general.

It used to be the case that a serious malady would require life-threatening or debilitating surgery; or medications so strong that they killed off beneficial as well as harmful bacteria and weakened the immune system to the point where Americans over age 65 average several different medications per day[1] —some primary meds to combat specific ailments or illnesses, and others to combat the harmful side effects of the primary (or secondary) meds.

Now, we are on the verge of being able to analyze not just a person's blood and other fluids, but that same person's exome (the less than 2 percent of DNA that codes for proteins), complete genome (all 3.2 billion nucleotide pairs), microbiome (our collection of mostly gut bacteria cells that outnumber our human cells), family history, lifestyle, and an increasing number of other factors (such as wearables and embeddable devices) that differentiate one human from over seven billion others, to precisely attack or even prevent diseases that once were fatal. One company recently claimed that more than a third of the people they analyzed were found to have a stage zero cancer or some other malady that could be cured now—prior to any discernable symptoms—that might not otherwise manifest for many years.[2]

A fetus can be scanned and genetic abnormalities, such as Huntington's Disease, might be cured before birth via CRISPR/Cas9[3] interventions. Some health and life actuaries I chat with are trying to extend their predictive analytics skills to bioinformatics and other new interdisciplinary fields to be a part of this action and contribute to more progress for humanity. Yes, this increases the bottom line for shareholders. Health companies can save expenses by paying only for the medications and procedures that will truly benefit the specific individual. Life companies can help their insureds live longer lives and extend the premium stream. Beyond the bottom line though, they are actively helping insureds to live both longer and more enjoyable lives.

As the actuaries at the forefront of these new technologies, we are certainly not one-trick ponies. The term unicorn comes to mind instead. Be proud to be a member of PAF!

- In this issue, Anders Larson summarizes some of the recent PAF achievements and initiatives that have catapulted us into the limelight as the fastest growing SOA section. His "Chairperson's Corner" highlights the section member preference for learning new tricks, techniques and even new subject areas; and how the council is listening and responding accordingly. Anders describes where we excel and where we still have room for improvement. See the exciting ideas he has for continuing our fabulous momentum.

- Next, I shamelessly … in fact, proudly, plug the September Predictive Analytics Symposium in my article "To be, or not to be … an Actuary." We like to think our newsletter is a valuable source for you to get up to speed on various PA techniques; but the PA Symposium will be an immersive experience that will quickly benefit all levels of actuarial attendees: entry level actuaries through senior managers, and PA newbies through advanced practitioners. Read, register, attend and reap the rewards of your increased capabilities.

- I initially talked about actuaries getting into epigenetics; but that is only one area where we can see actuaries embracing new disruptive forces rather than ignoring them and hoping they will go away. Nathan Pohle and Darryl Wagner describe automation as another opportunity for us. In their article "Why Actuaries Should Welcome Automation" they say, "for professionals like actuaries, technology—and namely automation to start with—creates many opportunities for those willing to embrace it."

- Most of these new opportunities involve some sort of predictive model; and model sophistication can vary widely. Brian Holland provides insights into how to choose the right level for your situation. In "Goldilocks and the Three Modelers" he shows the impact of adding complexity to spline regression models and to decision tree models. Brian introduces us to the bias-variance trade-off, which reflects the compromise between model complexity and predictive value. Ultimately, you have to communicate your results, and too much complexity can hamper that.

- In "How Credible is a Predictive Model?" Eileen Burns continues this thought process by addressing two very important considerations when evaluating a model: credibility and believability. No, they are not exactly the same; and Eileen explains how they differ and what they mean in the context of PA models. She also provides a summary of actuarial literature on the subject (much from former PAF newsletter issues) and she gives us her takeaway opinion of when they apply, and how to benefit from them.

- Further complicating the issue of how to explain a model is a host of different modeling languages and platforms. Some prefer R, others Python, MatLab, Octave, etc. and this exacerbates the "language" problem when reproducing results is necessary. Jeff Heaton shows us Predictive Model Markup Language (PMML) in his article "Introduction to PMML in R." Jeff summarizes the potential of PMML: "The standard format of PMML allows model deployment platforms to be designed without consideration to the original language that the data scientist chose to implement the model in."

- Dorothy Andrews gives us another glimpse of the changing landscape for insurance with her article "InsurTech: The Next Disrupter to the Insurance Industry." Dorothy discusses the Gartner Hype Cycle and its five stages from Innovation through the Plateau of Productivity, passing through stages such as the Trough of Disillusionment along the way. The National Association of Insurance Commissioners (NAIC) identified InsurTech as the number one threat to the insurance industry. It is yet another testimonial to why we need to put in the continual learning effort to be actuaries—and to reinvent what that means.

In this issue, we also have a reminder that PAF stands for more than just Predictive Analytics (PA). PA is great! But our section also covers Futurism (F). Disruptive technologies and movements can have great impact upon our industry and our profession, and we choose to think beyond just present technologies and attitudes.

The Actuarial Speculative Fiction contest typifies some unconventional projections of the future, and we are proud to be a long-time sponsor of this biannual contest. As a bonus in this issue, please enjoy a winning entry from our last contest, "Timeline," by Robert Ellerbruch. I like the speculative fiction stories mainly because they cause me to think about ideas I normally would not consider. For example, in "Timeline," one of the characters says, "You are correct that you can't predict the future, but you shouldn't extrapolate the inability to predict the future to mean that the future is not completely determined."

Regardless of how we may feel about free will vs. determinism, stories like this are thought provoking. Please consider writing your own story and entering it in the next contest. Here is a link to the contest site *https://www.soa.org/sections/2016-speculative-fiction-contest/*

Clearly, we are not a one-trick pony. We are a cavalry of cool ideas and great progress. My bet is on PAF to win in the first race … and the rest. ■

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ENDNOTES

1 *https://www.washingtonpost.com/national/health-science/the-other-big-drug-problem-older-people-taking-too-many-pills/2017/12/08/3cea5ca2-c30a-11e7-afe9-4f60b5a6c4a0_story.html?noredirect=on&utm_term=.07ec698fa9d0*

2 Craig Venter's company, HLI, claims to have "found serious detections in roughly 40 percent of patients, and many of the discoveries are found much earlier than they would have been found previously via traditional testing. They are finding cancerous tumors that are in phase 0 and 1 in patients who are experiencing no pain, whereas most people are often diagnosed in phase 4, where pain is prevalent and the disease is more difficult to beat." *https://www.cnbc.com/2018/03/27/genome-pioneer-craig-venter-is-trying-to-decode-death.html*

3 *https://en.wikipedia.org/wiki/CRISPR*

Chairperson's Corner

By Anders Larson

As you may be aware, the Predictive Analytics and Futurism (PAF) section membership has more than doubled in the past three years, faster than any other section in the SOA, and we want to be sure we are providing the value that our present-day membership is looking for. We had valuable information from a 2017 survey of SOA members who had recently left the section, but the sample size was relatively small and only represented the voices of the few members who were dropping their section membership. The section leadership felt an additional survey of current members was warranted, and in early 2018, we sent a voluntary questionnaire to all current PAF section members.

More than 250 of you responded, and in my opinion, you provided exactly the type of feedback we needed. In general, the feedback was positive, but we weren't just looking for a pat on the back. We wanted to understand what's working, what's not working, and what we can do to make the PAF section membership more valuable. After several months of review and discussion among the council members and friends of the council, we settled on two new initiatives that we are pursuing in response to your feedback, and I'm excited to unveil those initiatives to you here.

Asked why you joined the PAF section, 71 percent of you said it was to learn more about predictive analytics and futurism.

But before I get to the initiatives themselves, let's review some of the key points we took away from the survey results.

PAF members want to learn. Asked why you joined the PAF section, 71 percent of you said it was to learn more about predictive analytics and futurism, as opposed to staying up to date with SOA activities or networking. We believe we already have a strong focus on developing and providing educational content, and we intend to strengthen and expand our efforts in this area.

The newsletter is still our crown jewel. More than 45 percent of you were "very satisfied" with our newsletter, which was higher than any other specific area we polled. That's good to hear, because you'll be getting newsletters more often. Starting in 2018, we increased the frequency of newsletters to three times per year.

Hands-on is better. PAF members are interested more in the "how" than the "what." The material we cover is highly technical, and we need to find better ways to help members apply what they're learning to their job. Many respondents noted specifically that they were looking to us for hands-on guidance, either in person or in some sort of interactive format.

Networking and discounts to events are weak spots. These are the two areas where we had more "not very satisfied" responses than "very satisfied" responses. Starting in 2018, section members have free access to PAF-sponsored webcasts that are at least one year old and will get a $25 discount for all webcasts sponsored by the section during the year. We hope that these incentives at least partially address the concerns about discounts. Improvements to networking options, on the other hand, have not yet been addressed.

We're doing a pretty good job right now, but there is room to improve. Only 3 percent of members were not satisfied with their section membership, which is great news. However, 60 percent of you said you were "somewhat satisfied," compared to just 37 percent who were "very satisfied." Let's see if we can get those two numbers reversed in the next few years.

So, what are we doing in response to these findings? Well, first, let's be clear that we're going to continue doing much of what we have been: producing a newsletter, recording podcasts, sponsoring webcasts, planning the annual Predictive Analytics Symposium, and coordinating sessions at major SOA meetings. But we want to do more:

Jupyter Notebook Contest. We will be sponsoring a contest for section members to create a Jupyter Notebook document showing how predictive analytics techniques can be applied to actuarial problems. The top entries will receive prizes and their winning Notebooks will be posted on the PAF section web site.

Jupyter Notebooks are documents that contain both computer code (in Python, R or other languages) and rich text elements (paragraphs, equations, figures, links, etc.). They are simultaneously human-readable documents and executable documents that can be run to perform data analysis. We believe they have tremendous value as learning tools for our membership—the document can be understood and executed even by readers who are not yet proficient in the underlying programming language. The rich-text elements can allow the Notebook creators to illustrate exactly how an actuarial problem can be addressed with predictive analytics techniques. This is why we're posting the winning Notebooks on the PAF section website—not only do we want to celebrate the winning creators, but we want to use their work to help us all learn!

Hack-a-thon. At the conclusion or start of an SOA meeting (such as the Predictive Analytics Symposium), the PAF section will sponsor a multi-hour, free-form session ("Hack-a-thon") where meeting attendees can code against sample data, work collaboratively and receive guidance from predictive analytics experts. We believe the standard SOA meeting sessions are certainly valuable, but implementing these techniques takes practice. And that practice becomes much easier if you have others to help brainstorm and troubleshoot (as opposed to, say, Google-searching your error messages repeatedly).

We are in the preliminary planning stages right now, but we anticipate sponsoring our first Hack-a-thon sometime in 2019. Be on the look-out for more information over the coming months.

Again, thank you for making us the fastest-growing section in the SOA, and thank you for providing us with the feedback we need to continue adding value to your section membership. These new initiatives represent two more steps in our evolution, and we're excited to get started!

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“To be, or not to be” … an Actuary

By Dave Snell

Most of us are familiar with the choices posed in the soliloquy by Prince Hamlet, in Shakespeare’s famous tragedy.

Actuaries are facing a similar decision.

Some of us may choose to ignore the dramatic and accelerating changes taking place in the data science area, and their likely impact upon our profession. Like the blacksmiths who ignored the advent of cars, the camera manufacturers who laughed at the toy cameras on early smartphones, and the silent movie stars who thought the “talkies” were just a fad, we actuaries are in a profession that is facing disruptive forces and new adversaries. Their slings and arrows threaten to minimize or even eliminate demand for the skills we relied upon in the past. Perhaps some actuaries feel they will not be affected because they are already close to retirement; or they think their special niche area will always be needed. After all, there are still some blacksmiths, specialty cameras and silent movies. A few of us may survive anyway.

But what about the rest of us? Spreadsheet expertise no longer involves the ability to manually ensure that the sum of the row totals equals the sum of the column totals. Excel and other common tools can check this for you … or for anyone else, at very low cost. Commutation functions, once a major part of risk calculations, and understandable only by actuaries, are now essentially obsolete. How long will it be before a deep neural network or a random forest will eliminate the need for a pension actuary to compute retirement funding parameters, or a health actuary to optimize a provider group mix, or a valuation actuary to determine reserve requirements?

Sure, there are still areas where traditional actuarial expertise is necessary and they will continue to command high consulting or salary rates. But these are becoming narrower in scope, and the barbarians at the gate[1] are growing in numbers and acquiring more powerful weapons and tools to break into and take over our fortress.

Enough doom and gloom though! We have the expertise, aptitude, and opportunity to avoid this dystopian scenario by making the other choice—the choice “to be.”

“To be” an actuary in demand in this new world, we need to accelerate our learning process. This September, we have a wonderful panorama of ways to do that.

The second annual Society of Actuaries (SOA) Predictive Analytics (PA) Symposium is scheduled to take place September 20–21 in Minneapolis. Last year, a little over 250 of us attended the first rendition of this; and the attendee feedback was spectacular! Forth-eight percent responded that it was Excellent and another 46 percent that it was Very Good. Only 6 percent rated it Good or Fair and nobody disliked it. The energy was contagious. We were all excited and many of us felt somewhat like the proverbial kid in the candy store … so much to see and learn … so many choices. Fortunately, registered attendees received audio synchronized slides for most of the sessions. But the onsite experience added many more learning opportunities.

This year, instead of four concurrent breakout session choices, we have six; and each time slot has at least one session aimed at each of the three major tracks: manager/supervisor, beginner/implementer, and advanced practitioner. Many presenters from last year will return (with updated versions or new topics, of course) and many new topics and expert presenters were added. Once again, the SOA plans to record most sessions; but still, the chance to meet the presenters in person and ask them questions of most concern to you is a huge benefit, so you will want to choose your sessions accordingly. Facilitating this, we[2] have categorized each of the 48 breakout sessions by appeal to the specific perspectives.

If you currently manage a department and wonder how PA can help you gain or maintain a competitive edge, and how to hire a team or train your existing associates for maximum return on your investment, we have sessions for that (such as “Building (and Evolving Into) a Product-oriented Team” and “Delphi—The Time Tested Non-quantitative Prediction Tool”). If you have been reading the recruiting ads and wondering how you can leverage your actuarial skills and increase your personal market value by mapping out a plan to reinvent yourself, we have sessions to jump start your career development (such as “How an Actuary can Become a Data Scientist?” and “New Opportunities for Actuaries—Creative Thinking Inside the Box”). If you are already an expert at multivariate regression analysis and you want to learn the intricacies of deep neural networks to extend your reputation in PA, we have sessions for that (such as “TensorFlow Workshop” and “Opening the Black Box: Understanding Complex Models”). Even if you are already immersed in PA and happy with your current position,

we have sessions on best practices with newer tools to make your job even more fun and more productive, including ways to combine R and Python and leverage the best packages from each of them (such as "Jupyter Notebooks—The Opportunity to Consolidate Documentation, Multiple Programming Languages, Input and Output").

These are only a few examples from the dozens available. They range from new data sources (including epigenetics) through scaling your model for production use ("Commercializing a Data Science Model as API or Batch Service"). See the complete descriptions at the SOA registration site *www.soa.org/pasymposium*

Most of the tools (including programming languages) and techniques are free. The real cost of continued viability as an actuary in demand is the learning curve. Here, you get the opportunity to learn from, interact with, and form lasting personal contacts with experts in the specific areas of predictive analytics that best meet your professional needs.

Looking back, some blacksmiths adapted to the decline in horse transportation by forging wrought ironwork, sometimes even for cars. Some camera companies opted to partner with the smartphone manufacturers and sold millions of lenses to them to improve picture quality. Some of the silent movie stars worked on their vocal skills and transitioned into lucrative speaking roles. We can pick up and reinforce the predictive analytics skills needed to remain viable as the preeminent risk management experts for the insurance industry. And we can get a competitive edge on this with a small time and money investment this September.

It's a worthwhile investment "**to be**" an actuary. ■

Dave Snell, FALU, FLMI, ASA, MAAA, CLU, ChFC, ARA, ACS, MCP, teaches AI Machine Learning at Maryville University in St. Louis. He can be reached at *dave@ActuariesAndTechnology.com.*

ENDNOTES

1 *Barbarians at the Gate* was a 1993 movie about the competing forces in a leveraged buyout—of potential interest to actuaries involved in Merger and Acquisition work. It was also a famous quote from the 1999 Canadian movie "The Barbarian Invasions," which dealt with issues of the Canadian health care system.

2 I wish to publicly extend my thanks to my colleagues on the symposium's program coordination team: Anders Larson, Xaiojie (Jane) Wang, Rosmery Cruz, Stuart Klugman, Minyu Cao, and Kevin Pledge, as well as our company-specific representatives Sarah Hinchey and Adnan Hague, and the SOA event management team of Anna Abel and Agnes Czesak. They have generously donated many hours of work in the selection of topics and presenters to make this a memorable and productive experience for all attendees.

Trend Topic: Why Actuaries Should Welcome Automation

By Nathan Pohle and Darryl Wagner

Every day, there's a new headline about technology disrupting business—Uber and Lyft shaking up the taxi industry, robots replacing workers on the auto production line, self-checkout kiosks being put in and cashiers being phased out. It's a lot to take in, and the thought of technology replacing people can be unsettling.

However, for professionals like actuaries, technology—and namely automation to start with—creates many opportunities for those willing to embrace it. Instead of time spent on repetitive tasks or hours invested in spreadsheets, there is now the potential to set up parameters and have robotics perform some of this repetitive work. That means actuaries can focus more on the things that can advance our roles as strategic partners with an improved seat at the table.

In our consulting roles, we work primarily with insurance companies, and we're seeing a lot of them taking steps toward this kind of automation. Companies have started to automate actuarial processes ranging from actuarial model setup and run processing to how they populate content in memorandums and reports.

The processes we follow and our day-to-day tasks will change, but our commitment to our stakeholders and our professional standards must remain steadfast. We cannot blindly trust output from machines. In a world where more and more work is done by machines, we must learn to interact with that work, critically assess it, and spend relatively more time in a review capacity.

For example, instead of spending time running and re-running financial models, actuaries can spend more time reviewing sensitivity testing to see whether the model results make sense. And when we shift our efforts to work that truly can't be done by machines, the work we perform and manage and the results we produce will be both more efficient and more valuable for our employers, clients and other stakeholders, including the public.

The ripple effects from changes in the way work is done will also impact how we source and develop actuarial talent to meet the future needs of the profession. As we apply technologies from outside of traditional actuarial software packages, actuaries will need to expand their technology skillset. When we automate processes from which junior actuaries would have typically "learned the ropes," we need to rethink how actuaries learn and develop, particularly at the more junior levels in their careers (e.g., more focus on an apprenticeship model). In addition, when we fundamentally change how actuaries work from less stewardship activities to more strategic counsel, the skills for an actuary will need to evolve.

These changes will not happen overnight, of course, but we need to start planning now, so we are prepared for the future. That includes reimagining both the core skillsets for actuaries and the opportunity for greater added value in our work, updating our education and development systems, planning for workforce changes and undertaking a bit of change management ourselves. And most important, we need to understand how to strategically educate our stakeholders about the advantages the actuary of the future can help them achieve.

Quite simply, as our workload shifts away from raw computation, our jobs will expand and evolve, not evaporate. While understanding how to perform manual calculations and build models is, and always will be, important, we can potentially make a bigger impact by predicting risk, testing our assumptions and helping people and companies mitigate and capitalize on that risk to avoid undesirable outcomes and optimize results.

We are helping insurance companies expand their capabilities for actuarial people, process and technology through our firm's Exponential Actuary solution. The insurance industry is in the early stages of disruption both broadly and in the context of the actuarial profession. Although certain insurance organizations and departments have been early adopters and are blazing trails, the majority of the change—and opportunity—is in front of us. By adopting these enablers and new business models, the future outlook for the actuarial profession is bright. It will enable actuaries with the right skillsets to add greater value to organizations through more strategic activities. ■

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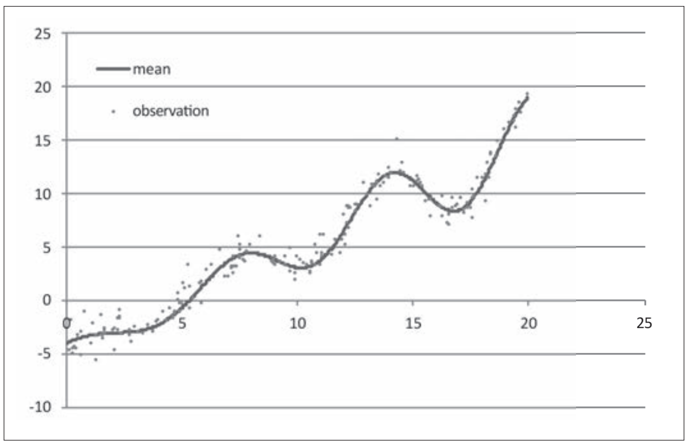
Goldilocks and the Three Modelers

By Brian Holland

It is no news that computing power is now cheap. However, this has created a new problem: when to stop modeling? It is easy to try out many different models. We intuit that it is a bad idea to have overly complex or simple models. They should be just right. But what does that mean, and how do we tell? This brief note is a reflection on an issue that we know we have, and an attempt to socialize some concepts and terms to describe it that will help the actuarial community address the issue in forming opinions about assumptions.

A construed example will help to illustrate the issue (Figure 1). We want to find the mean of the points: the black line is the underlying mean. The points could be functions of observed decrements or something else, it hardly matters for an example.

Figure 1
Construed Example: Y = 0.1 x sin x + 3 exp(-x) cos x + 0.1 Z



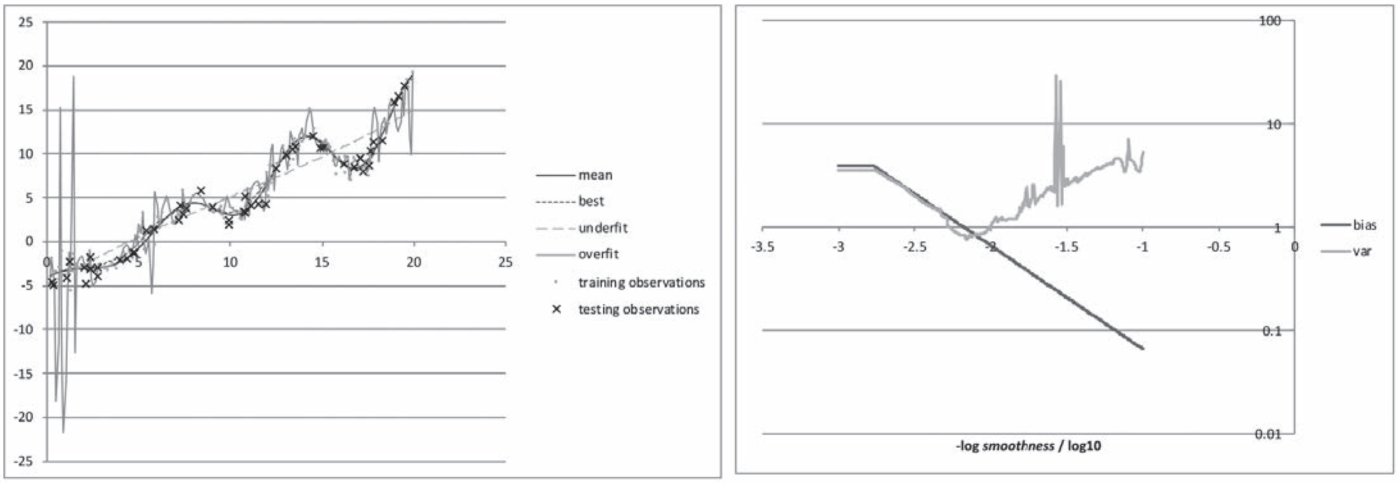
What will make a model "just right" is whether it predicts better than alternatives. To find one, we can take most of the observations, train a model on those, and test the model on the remaining samples. We can compare between different classes of models, or tune models within one class by means of a "metaparameter" that is used to adjust the level of complexity. Two examples follow: spline regression and a tree model. The important point is that whatever type of model we try, we have this issue of model complexity: choosing which features to use in varying mortality slope, or something more elaborate.

A CONTINUUM OF OPTIONS: SPLINE MODEL

The spline regression model[1] is especially nice for this sort of comparison. The metaparameter in this case is used to specify the smoothness of the curve. The higher the smoothness is, the lower the wiggliness, and vice versa. Figure 2 shows three spline regressions versus the data: one underfit, one overfit and one in between. The underfit curve is only a straight line. Smoothness is high, so wiggliness is low. The overfit curve hits almost all the training points—but that is hardly good! That means it is too complex, and will not fit the new data well. It overfits the training data. Goldilocks might say that one bed is too smooth and hard, while one is too soft and lumpy. We can compare those models on a continuum, shown on the right. The mean squared error (MSE) on the training data is the bias, while testing MSE is the variance. The underfit model uses the parameter on the left side. Note that the metaparameter is transformed so the simple model is on the left and the complexity increases to the right—that is the customary presentation. There is a trade-off between model complexity and predictive value. This trade-off is called the bias-variance trade-off. Some additional complexity helps, but after a point, it hurts the predictive value of the model. The best fit model shown on the left is the one at the minimum variance. In the bias-variance trade-off, additional complexity reduces the bias, or error on the training set.

In this case you can see some static due to numerical precision issues in the variance graph—it would ideally decrease and then increase fairly smoothly. I've left those blemishes in this presentation because you are also likely to see that sort of thing in your own experiments.

Figure 2
Spline Regression



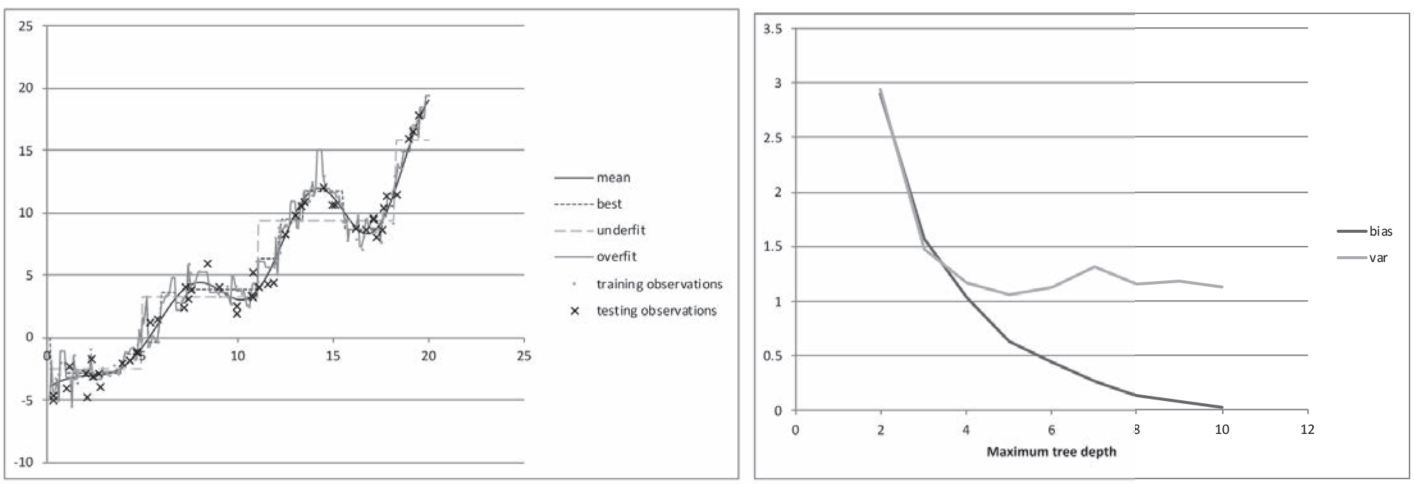
ANOTHER EXAMPLE: TREE MODEL

As actuaries recommending assumptions, we need to remain cognizant of the bias-variance trade-off and its implications for the predictive value of assumptions. This issue is present regardless of the model type. Figure 3 shows the same trade-off for a tree model. A tree model is used to split the data at a certain point to minimize error on each side of that point, using the simple mean on each side as the predictor. Then, if an additional split reduces the error further, the tree will split again. In this example the metaparameter is the maximum depth, or number of splits, that the tree is allowed to make. The underfit case is allowed at most two splits, so 4 = 2*2 averages for sections of the line. There is clearly more going on in the data and more splits will help predictions. Allowing up to 10 splits allows the model to reach out and grab the outliers, which would be poor predictions for neighboring points. The optimum value in this case is about five splits at most, i.e., 32 segments of the line. There are only 150 training points out of the 200 total, so a tree depth of seven, which allows 128 segments, allows a local space around nearly each training point and the deeper models are about the same.

COMMUNICATION

Actuaries have another job besides forecasting: communicating their decisions. That job can be at least as important. I would assert that using such demonstrations as the bias-variance trade-off will help actuaries show why they have chosen a particular degree of complexity. That justification is especially important given that a degree of art and judgment will remain in our work.

Figure 3
Decision Tree



The responsibility to communicate points us to another trade-off: not just model complexity, but communication complexity. It can take some practice to be able to wing a pithy explanation of model complexity to professionals from other spaces, such as accountants. Using a simple average or linear regression is simple to communicate, but a penalized spline model is less so—especially if discussing the choice of penalty. In this context I like to think of complexity as length of the story. A simple story is a short story, a more complex story is longer. Depending on the assignment, a simpler story might be better than a more (quantitatively) predictive but longer story. Various complexities will come up in absorbing these techniques in organizations where the techniques are unfamiliar, possibly starting with the model results if a different random subset of training data is chosen. The organizational learning curve can be long. I find it helpful to remember that we are only predicting anyway; we're just trying out how well those predictions work in advance.

Among practitioners, summary statistics can certainly facilitate communication: cross-validation statistics, AIC, or BIC, for example, get at the same underlying issue of model complexity versus predictive value.

DÉJÀ VU ALL OVER AGAIN

By now you might be wondering what seems so familiar about this issue. The model complexity trade-off is nothing new to actuaries. Whittaker-Henderson type B includes two components in its objective function, combined with a weight: a fidelity, or fit, component describing model error, and a smoothness parameter. Henderson published this approach in 1923. It was computationally expensive. These days, of course, computation should not be an issue. For a nice discussion and comparison to current methods, please see "Back to the Future with Whittaker Smoothing" by Iain Currie, *https://www.longevitas.co.uk/site/informationmatrix/whittaker.html*.

The bias-variance trade-off even appears in *Transactions of the Society of Actuaries*, 1995, Vol. 47 in "Graduation" by Kernel and "Adaptive Kernel Methods With a Boundary Correction" (Gavin, Haberman and Verrall). So, it is nothing intrinsically new in our space and is certainly fair game.

CONCLUSION

Actuaries continually face choices in assumption complexity. The conceptual framework provided by the bias-variance trade-off can help actuaries communicate their choices between overfit and underfit in their search for a model that is just right. ■

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ENDNOTE

1 *https://docs.scipy.org/doc/scipy/reference/generated/scipy.interpolate.splrep.html*, please try it out yourself.

How Credible is a Predictive Model?

By Eileen S. Burns

One of the outstanding questions the life insurance industry must face in the adoption of predictive models is how to translate the understanding stakeholders have with respect to current methodologies into this new framework. In this article, I enumerate several key reasons why companies struggle to gain comfort with new methods, note the open mathematical questions we face, and report on a few recent publications offering specific ideas to answer them.

WHY THE TROUBLE?

1. To start, there is confusion on the **terminology**. What does it mean to be a predictive model? I'll keep it simple. There is a denotation and a connotation for the term predictive model. I loved these terms when I learned them in school, and this is a perfect example of why they are both important. The denotation is that the model predicts the future. All actuarial projection models do this. So what's the difference? The connotation is that it is a model built on past experience, leveraging advanced analytical methods, to generate improved confidence in future predictions over less advanced methods.

   The "advanced" analytical methods can run the gamut from fairly simple to a place where a degree in complexity science is required. Logistic models have been around for ages, the benefit here is to use their ability to leverage smaller amounts of data as linear predictors, rather than keeping everything categorical, which slices data into tiny pieces that lack credibility. Or they can be as advanced as ensemble models built via machine learning. These are powerful methods, though they struggle with interpretability and potential for overfitting. Going another direction, there are agent-based models. These attempt to address the "why" which so often evades statistical analysis. Correlation is not causation—a statistical model can only confirm likely correlations. An agent based model aims to describe why agents (policyholders, agents, insurance companies, etc.) act as they do using causal relationships. They test these relationships on past data in order to parameterize a set of rules.

   All such models can offer improvements over traditional methods, assuming the model builders respect the requirements of stakeholders.

2. Then there is confusion on the term **predictive**. In name, it simply means estimate what will happen in the future. The trouble is when it is interpreted to mean more. For example, sometimes we lack the past experience to generate a model as described above. Can a predictive model solve this issue? Nope! No model of the past decade will be parameterized based on vast quantities of past data that includes rising interest rates. Any model parameterized on recent data that is used to predict responses when interest rates rise will be extrapolating. As with traders in the stock market, some of these models are likely to make accurate predictions, and some are likely to fail to do so. A modeler who guarantees accurate predictions is like the hedge fund guaranteeing a 15 percent return. But a modeler who tells you the underlying assumptions, and offers guidance for how to gain comfort in those predictions as well as in their uncertainty … they can allow you to face that uncertainty with eyes wide open, and isn't that what actuarial judgement is all about? Yes.

3. Finally, there is confusion around how **credible** predictions can be. Given the last few paragraphs, this should be an obvious concern. It is made worse by the fact that there is not a one-to-one comparison between "credibility" and "believability." That is, the credibility we are accustomed to quoting as actuaries, that is based on the quantity of observations in a given category, is not easily comparable to the believability of the prediction that comes from a predictive model. This question is different from the first two as it requires a mathematical answer.

So how do you decide to believe in a model that may be of any form, is based on past data and possibly a few educated assumptions, when your trusted forms of credibility aren't relevant? And secondly, if you determine that your assumption is not fully credible, what options do you have?

I'm so glad you asked!

The remainder of this article gathers industry commentary on two questions.

1. **Credibility measurement:** How do we quantify the believability of a data-based assumption?
2. **Credibility blending:** If we determine we don't have enough confidence in assumptions based on our own data and models, what options do we have for leveraging external data and models?

BACKGROUND

In 2013, the Actuarial Standards Board published a revision to "Actuarial Standard of Practice Number 25: Credibility Procedures," expanding practice areas covered to include life and pension. The standard addresses both of these questions. It describes the responsibility of actuaries to ensure that there is adequate care taken in assessing credibility or blending experience, areas of such procedures where an actuary may need to use judgement and related considerations, and in Appendix I lists several currently used methods for assessing credibility. Beyond the scope of practice areas, the notable addition to the latest draft includes a new category "Emerging Practice Involving Statistical Models."

RESOURCES

The guidance provided in ASOP 25 is intentionally minimal, merely allowing for the actuary to use judgment in deciding which methods are most appropriate for a given application and requiring adequate communication. There are two good resources (1 and 2 below) for actuaries to learn more about their options and see applications of a few methods, however they concern only older methods not those mentioned as "Emerging Practice." Luckily this topic has started to gain the attention of predictive modelers. I'm aware of four more recent publications (3–6 below) that offer motivation for addressing the issue of credibility, and/or possible solutions.

1. "Credibility Practice Note," American Academy of Actuaries, July 2008, Robert DiRico et al.

   The first two sections provide some motivation for revisiting credibility, and an amusing recap of state variations in requirements related to credibility. The third section discusses Limited Fluctuation and Greatest Accuracy (aka Buhlmann, aka Empirical Bayesian) credibility in detail, and addresses strengths and weaknesses of each. It also offers examples related to mortality, lapse, and reinsurance pricing, and a couple of cautionary tales, lest you start to think credibility can be straightforward. The last two sections can be seen as a resource—offering a short history of credibility theory and an extensive bibliography.

   Takeaway: This is a comprehensive resource for understanding how to apply two common types of credibility analysis (measurement and blending) and potential complications in applying them.

2. "Credibility Theory Practices" by Stuart Klugman et al. in December 2009.

   This was published in 2009, seemingly as an attempt to encourage more life companies to consider implementing credibility. "Statistical credibility's rigor can validate or improve actuarial judgment applied to company experience data."

   It presents thorough examples (with accompanying spreadsheets) for both limited fluctuation and Buhlmann credibility. The examples highlight the differences between the two methods when applied to A/E ratios for individual companies relative to the industry experience. The conclusion emphasizes that these differences stem from two important features of a block of business: the difference between its mean and the population mean, and the variation within the block about its own mean. The paper also includes a thorough bibliography.

   The publication consists of both the paper and a survey of 190 insurers "to find out the level of understanding in the industry, actuaries employed by U.S. insurance companies were surveyed to ascertain who uses credibility theory and how credibility theory is applied at responding insurers."

   Takeaway: This is a very practical article describing the same two common types of credibility analysis (again, both measurement and blending) with straightforward examples that allow easy comparison between the two.

3. "Is Credibility Still Credible?" Mark Griffin, *Risk Management*, August 2017.

   In the Joint Rrisk Management Section newsletter, Mark Griffin raised this question citing motivation from PBR, IFRS, Solvency II, and Embedded Value. He uses a simple example to highlight the need for a method that supports use of a company's data when it is the most relevant data available, explaining that some methods would argue otherwise. He rejects the out-of-the-box version of limited fluctuation credibility that would mandate a minimum of 1537 claims based on confidence of at least 95 percent and tolerance of at most 5 percent. He argues a hypothesis testing paradigm makes sense.

   Takeaway: If you need inspiration to reconsider how you are approaching credibility analysis, this is the article for you.

4. "Logistic GLM Credibility," Matthias Kullowatz, *Predictive Analytics and Futurism*, December 2017.

   My colleague Matthias Kullowatz notes that a predictive model such as a logistic GLM, generates probabilities, as well as confidence estimates, allowing him to reframe limited fluctuation credibility within the hypothesis testing framework. He laments it is still left to the actuary to set appropriate confidence and tolerance bounds, and discusses other issues such as the assumption of asymptotic normality and link function complications. He alludes to a method for determining credibility of an estimate relative to one from an industry population with "full credibility."

Takeaway: The article presents a proposal for using limited fluctuation credibility through a hypothesis testing framework to measure credibility in terms of statistical confidence. It is an easy extension to note that upon selecting confidence levels that constitute full and no credibility, this can then be used to blend models between company and industry experience.

5. "Calibrating Risk Score: Model With Partial Credibility," Shea Parkes and Brad Armstrong, *Predictive Analytics and Futurism*, July 2015.

   Shea Parkes and Brad Armstrong demonstrate a model for credibility that goes straight to blending of experience to calibrate risk scores for smaller blocks of policies. "Instead of estimating completely new weights, it is possible to use a technique known as ridge regression to only adjust the coefficients that are credibly different for the target population." They further describe that the method can be tuned to vary the weight given to each of the target and the reference. They discuss validation methods for such smaller blocks, and variations among ridge to lasso to elastic net regressions. The paper includes reference to a package in R.

   Takeaway: The article presents a proposal for using ridge regression to generate estimates for a small dataset that may differ from a larger reference set, but without losing the power of the reference dataset's credibility. Credibility measurement and blending is done implicitly through the model.

6. "Parameter Uncertainty," Brian Hartman et al., CAS, CIA, SOA Joint Committee, April 2017.

   This paper was published in 2017 by a cross-body joint effort of the CAS, CIA and SOA. In it Brian Hartman et al. give a comprehensive view of parameter uncertainty explaining "understanding the uncertainty associated with model estimates is essential to properly quantifying risk." While they don't mention credibility explicitly, the fundamental question addressed is the same—how much faith can you put in the estimates from your model? In the life context, they look at mortality rates, mortality curves, and single premium immediate annuity values. They propose a Markov chain Monte Carlo (MCMC) method to estimate the posterior variability of outcomes for a hypothetical block. The paper has additional examples pertaining to health and P&C that, as a non-practitioner, I will leave to you to explore.

   Takeaway: The paper proposes an MCMC method to estimate the likely breadth of possible futures, essentially, a confidence band around the best estimate. As with the Kullowatz article, the method could be used to blend models between company and industry experience, or alternatively could be adapted to consider company data as the sample data and consider the posterior estimate to be the final estimate.

CONCLUSION

You can see we're starting to chip away at the iceberg, but there's more to do. Specific topics to address include other ways to blend models, how to document actuarial judgment required, and how to determine when such judgments can be statistically tested. It would also do us well to standardize methods for the new options now listed in ASOP 25 for various emerging model forms, for which it states: "credibility can be estimated based on the statistical significance of parameter estimates, model performance on a holdout data set, or the consistency of either of these measures over time."

Our section is full of those who are interested in developing and applying new modeling methods, and as actuaries, we are still suited (and required) to explaining how the results should be understood and used. As we continue to push the envelope here, we'll need to continue to enhance our communication of what we've done.

Please send me a note if you are aware of publications on other methods for credibility analysis that we should add to the conversation, or if you want to write one of your own in an upcoming PAF newsletter! ■

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Introduction to PMML in R

By Jeff Heaton

Predictive Model Markup Language (PMML)[1] is an Extensible Markup Language (XML)–based predictive model interchange format originally introduced by Dr. Robert Lee Grossman, who was at that time the director of the National Center for Data Mining at the University of Illinois at Chicago. Models produced in R, Python and other platforms can be exported to PMML. Once in PMML, these models can be executed on a variety of other platforms to produce scores.

A platform's PMML capabilities are described as being a consumer or a producer. Some platforms are both producers and consumers; however, most only support one side. For example, the R programming language can function as a producer, but not a consumer. This means that a random forest that was trained in R can be exported to PMML. However, the PMML saved by R cannot be loaded by R. Because of this, PMML is not a sort of general purpose file format. The primary purpose of PMML is to allow a trained model to be exported from a development language, such as R, Python or another language to be executed on a production language such as Java or Scala. In this way, PMML is more of an export format for deployment. The PMML website contains a list of what platforms are producers and consumers.[2]

> The primary purpose of PMML is to allow a trained model to be exported from a development language.

PMML CAPABILITIES

Once a model has been properly trained, it is desirable to save the state of that model. If the model is not saved, then it will be necessary to retrain each time the model is needed. Such retraining is undesirable on several levels. Firstly, it might have taken many hours of computer runtime to have trained that model. Secondly, there is a stochastic element to the training of many models. Saving the model's internal state is often the only way to reproduce the results of a particular model. Modeling frameworks provide a means of saving the state of your model.

The model's state is whatever the model needs to produce a score. For a GLM the state includes the coefficients, intercept and choice of link function. For a random forest, the state would include the tree structure and any values used to calculate the score. Programming languages, such as R and Python provide a means of storing this model state. R stores these models to RData files and Python uses the Pickle file format.

It might be tempting to think of PMML as another file format to store your model in, similar to RData or Pickle. However, this is not exactly the case. I do not suggest that you use

PMML as a replacement for Pickle or RData. One obvious problem is that R only has the ability to write PMML, not read it—at least with the most popular free PMML libraries. Because the conversion to PMML might be a one-way trip for many programming languages, PMML is not a desirable alternative to that language's native format. Another difference between PMML and RData/Pickle is that preprocessing and ensemble information is encoded into PMML.

Your data will likely require some preprocessing before they are sent to the model. Continuous values might be normalized to a z-score. Categorical values might be encoded as dummy variables. When a model is stored as a RData/Pickle file, this encoding is not saved as part of the file. A PMML file attempts to encode the entire pipeline of data processing for your model. This includes common preprocessing steps, such as normalization, dummy variables, and dealing with missing values. PMML can also store the pipeline used to ensemble multiple models together. Because PMML focuses on encoding the entire pipeline, PMML is primarily a storage format for deployment. Once your model's pipeline is encoded into PMML, it can be deployed with a number of different open source and commercial products.

One popular open source deployment package for PMML is OpenScoring.[3] The OpenScoring framework can deploy PMML files as restful web services. These web services can be accessed by other programs, even those that are outside of your company. All communication with your deployed web service occurs using the JavaScript Object Notation (JSON). This allows other applications, written in nearly any programming language, to interact with your model. The programming language that you originally produced the PMML from is not important.

Because PMML is a standard, it requires that each model type that you seek to use to be covered by the PMML standard. Because of this, you might not have access to the latest models or new features from existing model types. However, unless you are producing models using bleeding edge technology, this is often not a problem. For example, the list of supported models for the R programming languages include kNN, Mining Models, Regression Models, General Regression Models (including Cox), Neural Networks, Decision Trees, Clustering Models, Association Rules, Support Vector Machines, Multinomial Logistic Regression, Random Forest, Random Survival Forest, and Naïve Bayes Classifiers.[4]

EXAMPLE: EXPORTING A RANDOM FOREST IN R

In this section, a sample R script to produce PMML is examined. This code, along with the resulting PMML, can be found at the author's GitHub page.[5] This example creates a random forest and trains it against Fisher's Iris Dataset.[6] The example code is provided here:

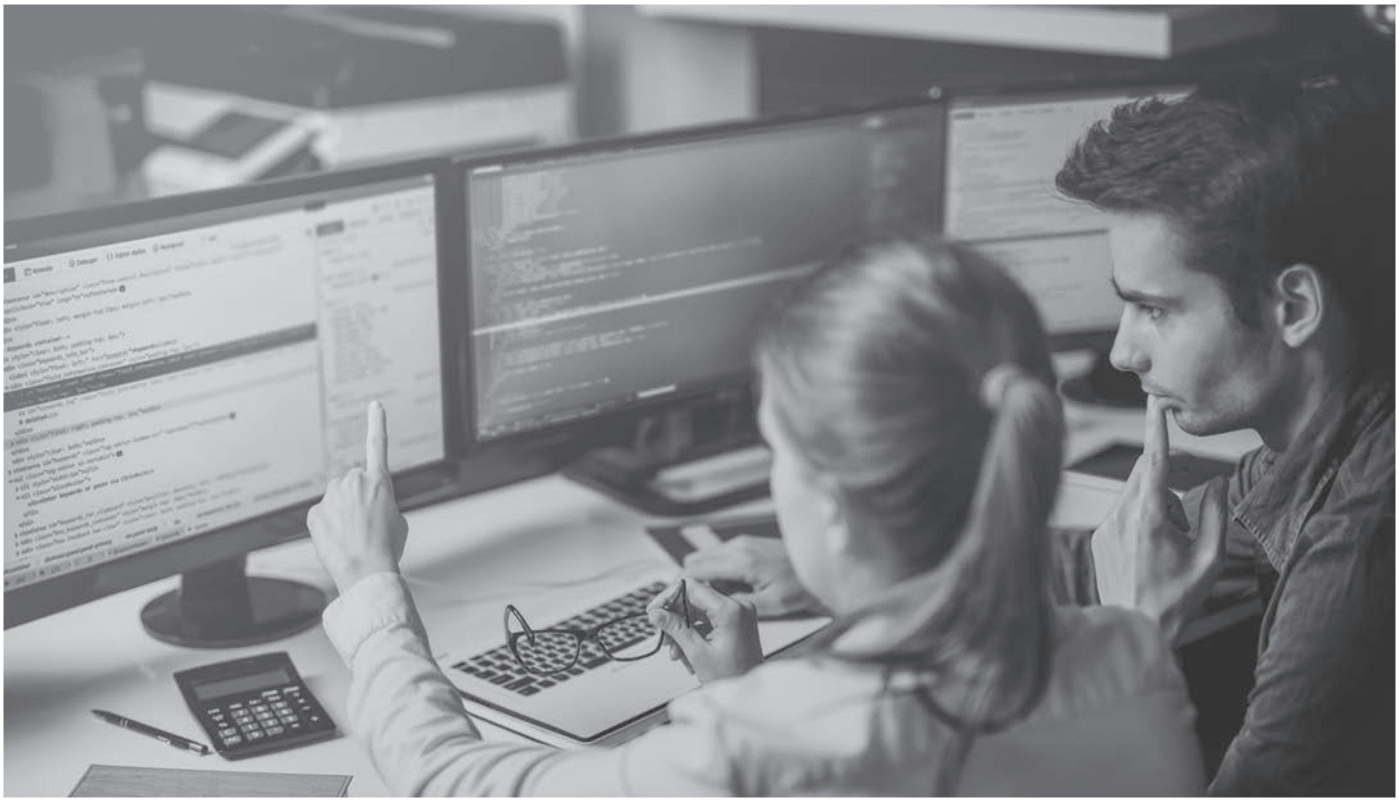
```
# Libraries
library(randomForest)
library(XML)
library(pmml)

# data to build model on
data(iris)

# train a model on a 75-25 split between
training and validation
z <- sample(2,nrow(iris),replace=TRUE,
prob=c(0.75,0.25))
trainData <- iris[z==1,]
testData <- iris[z==2,]

# train model
rf <- randomForest(Species~.,data=trainData,
                   ntree=100,proximity=TRUE)
table(predict(rf),trainData$Species)

# convertto pmml
pmml <- pmml(iris_rf,name="Iris Random
Forest",data=iris_rf)

# save PMML XML
saveXML(iris_rf.pmml,"iris.pmml")
```

The random forest is created with the common R library named simply RandomForest. Once the random forest is trained, it is encoded to PMML using the R PMML library that can be obtained through the Comprehensive R Archive Network (CRAN). Once the model has been encoded to PMML, it can be saved to a file with the R XML library.

The entire PMML file is verbose and lengthy. While the file is not reproduced here, it can be viewed at the author's GitHub repository.

Now that the random forest has been saved to a PMML file, it can be deployed as a restful web service with a PMML server, such as OpenScoring. This allows other applications to send JSON, such as the following, to receive an iris prediction.

```
{
"petal-width": 1.1,
"petal-length": 2.2,
"sepal-width": 3.3,
"sepal-length": 4.4
}
```



A result from the model might be as follows:

```
{
"prediction": "Iris-versicolor"
"confidence": .83
}
```

For a complete guide to setting up a restful web service to score PMML refer to the URL previously given for OpenScoring.

CONCLUSION

PMML is a standard file format that is typically used to encode models for deployment. The standard format of PMML allows model deployment platforms to be designed without consideration to the original language that the data scientist chose to implement the model in. If you seek to deploy a model with PMML it is important to ensure that the model type that you make use of is supported by the PMML client that you will ultimately deploy your model on. ■

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ENDNOTES

1 *http://dmg.org/pmml/v4-3/GeneralStructure.html*

2 *http://dmg.org/pmml/products.html*

3 *https://github.com/openscoring/openscoring*

4 *http://dmg.org/pmml/products.html*

5 *https://github.com/jeffheaton/present/tree/master/SOA/paf-newsletter/2018/pmml*

6 *https://en.wikipedia.org/wiki/Iris_flower_data_set*

InsurTech: The Next Disruptor to the Insurance Industry

By Dorothy L. Andrews

InsurTech is a portmanteau of the words "Insurance" and "Technology" and refers to technology that mediates insurance transactions between consumers and insurance companies. These firms are exploiting the lack of inertia in traditional insurance systems by challenging age-old marketing, underwriting and pricing of insurance products. They are proving transacting insurance products is no different than transacting widgets, creating disruption to an industry thought navigable only by specialists such as actuaries, accountants and medical underwriters. The application of InsurTech is marked by the innovative use of technology to transform the insurance customer's buying, underwriting and in force management experience by replacing traditional constructs of insurance with technology driven systems that use big data and big data analytics that are independent of the "old-school" approaches (Kocianski, 2018). This paper will discuss the current state of InsurTech, the reliance on big data and big data analytics, and the implications for the insurance industry.

> Contrary to popular notion, the term "big data" has a history that dates to the 1990s.

Contrary to popular notion, the term "big data" has a history that dates to the 1990s (Lohr, 2013). Lohr (2013) reports that the earliest use of the term with a meaning similar to its current usage was by chief scientist of Silicon Graphics Incorporated (SGI), John Mashey. John Mashey gave a presentation titled "Big Data ... and the Next Wave of InfraStress" to the USENIX Association, the Advanced Computing Systems Association. His presentation discusses the issues of storage, bandwidth, memory, user expectations, system environment and other issues that remain relevant today in working with big data. Since the Mashey presentation, the term "Big Data" has also become known for its ubiquitous influence on consumer transactions and social media interactions, and for igniting discussions about data privacy, getting unwanted attention from regulatory agencies.

The hype surrounding big data is studied and tracked by Gartner Inc. using the Hype Cycle. (Gartner, 2017). Gartner claims to be the "best first source for addressing virtually any IT issue because of [their] world-class, objective insight, the rapid access to that insight, and the low cost compared to the impact and other alternatives (Gartner, 2017, p.1)." Gartner Hype Cycles are graphical representations of the life cycle and adoption of various technologies and their applications. There are five stages to the hype cycle. They are: 1) innovation (or technology) trigger, 2) peak of inflated expectations, 3) trough of disillusionment, 4) slope of enlightenment, and 5) plateau of productivity. Placement in the cycle reflects relevancy to real world problems. The methodology attempts to trace the evolution of an innovation from a novelty stage to its ultimate maturity as either a vital business agent or an over-hyped innovation that did not pan out.

Gartner defines each of the stages. The innovation trigger is the breakthrough moment, where there is a lot of "buzz" but no evidence, necessarily, of effectiveness. As the attention increases, the innovation reaches its peak of inflated expectations, with a number of successes as well as failures. The trough of disillusionment follows if the innovation fails to live up to its early promise. Continued investments to improve the product can move the innovation into the slope of enlightenment, where the application of the innovation becomes more pervasive as a viable solution to a business problem. If the plateau of productivity is reached, the innovation is widely viewed as necessary to operations and the investment in the technology is improving a company's bottom line.

Big data moved from its innovation trigger phase in 2012 and dropped into a trough of disillusionment by 2017.[1] It is noteworthy that big data was dropped from the hype cycle in 2015 because it was felt that it was no longer an emerging technology, as opined by the analyst who created the 2015 hype curve (Woodie, 2016). Big data returned to a position of disillusionment in the 2017 Gartner hype cycle. However, Bennett (2017) of Thompson Reuters has a more optimistic view of the market maturity of big data. Bennett feels big data is "well beyond disillusionment and moving into productivity—but that comes with the caveat that this is just another tool in the box (p.1)." Bennett's view of big data includes analytical tools and machine learning algorithms to access, process and mine big data for information. Gartner's definition is more limited in scope and restricted to defining big data in terms of three Vs: volume, velocity and variety (Sicular, 2013).

Currently, big data is defined in terms of the five Vs (Cano, 2014; Jain, 2016; Leboeuf, 2016). They are:

- **Volume:** The size of the data set
- **Velocity:** The speed at which data is available
- **Variety:** Use of nontraditional insurance data
- **Veracity:** The reliability of the data
- **Value:** The monetary contribution of the data

INSURTECH APPLICATIONS

InsurTech applications use big data and big data analytics to transform the insurance buying, underwriting, and in force management experience. Some highly recognized InsurTech organizations who are the early catalysts of change in the insurance industry, include:

- Lemonade Insurance Company. It changed the customer buying experience through InsurTech cell phone applications (Fromm, 2017). The app driven experience underwrites insurance policies by utilizing big data-based algorithms to issue policies in less time than consumers have experienced under traditional underwriting of the past. Paying claims is lightening quick as well (Lemonade, 2018).

- Haven Life, a Mass Mutual insurance company, is deploying life insurance applications using InsurTech devices and approaches (Huckstep, 2017). It deploys big data, big data analytics, AI and other machine learning tools to speed up the underwriting and issuance of term life insurance policies (Dignan, 2017).

- InsurTech consulting firms are cropping up in the life insurance space to address the challenges insurers are facing to understand the evolutions currently taking place in the marketplace. Attracting and retaining new customers is the number one priority of insurers in this new age of technology driven devices transforming the customer engagement relationship (Cision PR Newswire, 2018).

The industry may be ripe for these innovations, but many incumbent players remain reluctant to adopt them (Satter, 2018). Insurance is a highly regulated industry with many layers of jurisdictional legal baggage to deal with. Regulators are still developing their own expertise in big data and big data analytics and may be resistant to relaxing regulations before their education is complete, despite the arrival of these innovations. Insurance companies understandably may err on the side of caution and shy away from start-up ventures rather than risk regulatory challenges. Many of the InsurTech startups still require the help of traditional insurers to handle underwriting and manage catastrophic risk. However, insurance is dependent upon consumers and as more InsurTech startups garner consumer interest with a more refined, technology enabled and savvy behavioral approach, insurers will figure out how to harness these technologies and work to develop actuarial standards of practice to satisfy regulatory concerns to safeguard consumer protections.

DISCUSSION

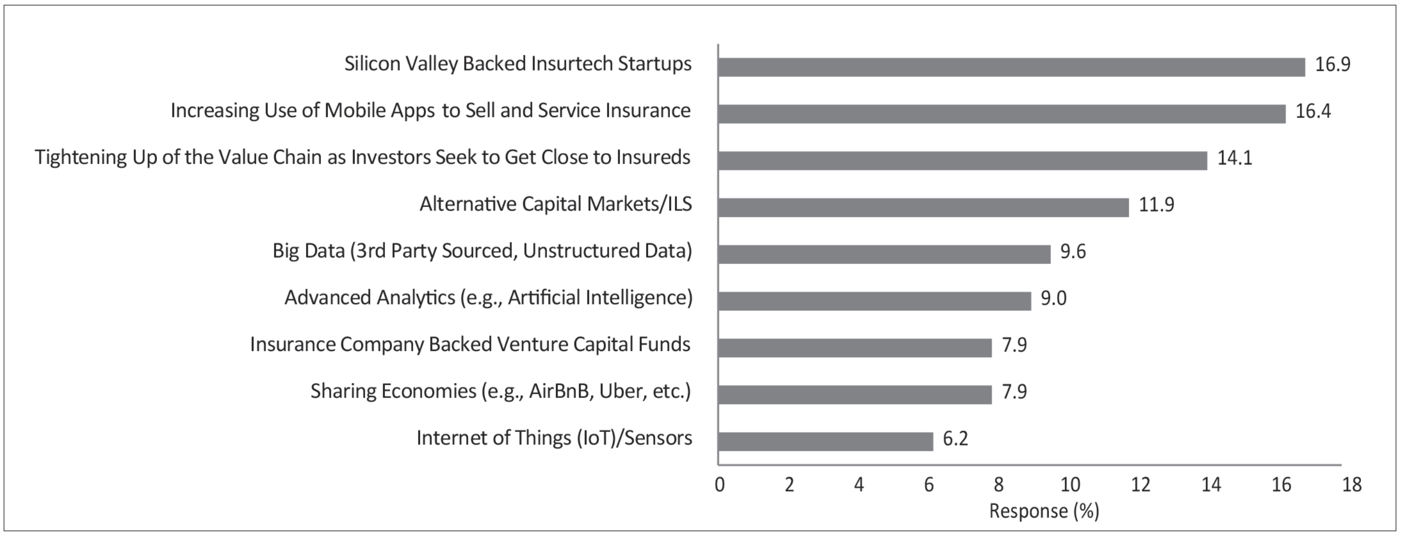
Over the last few years, InsurTech startups have grown to more than 1,500 firms, with funding more than a $1 billion for three consecutive years ending in 2017 (NAIC, 2017). The National Association of Insurance Commissioners (NAIC) is closely monitoring these firms for the disruption they pose for the industry. At the 2018 Spring NAIC Meeting in Milwaukee, Wisconsin, the American Family Insurance Company made a presentation to the Innovation and Technology (EX) Task Force of the NAIC (NAIC, 2018). The presentation identified the greatest threats to the insurance industry and InsurTech was identified as the number one threat (Fig. 1), as summarized from A.M. Best data and research. The third largest threat is interesting in that it identifies investors getting "close" to insureds. The threat posed is to the traditional agent mediated relationship between the insured and the insurance company. This threat suggests the agent is being displaced and this displacement will eliminate a huge revenue source for agents, commissions on insurance premiums, which is also a huge expense for insurers. Therefore, displacing agents with technology has huge potential expense savings for insurance companies.

There is a need to evaluate the risks these innovations pose to the continued health of insurance organizations. The American Academy of Actuaries (AAA, 2018) released a monograph on Big Data and the Role of the Actuary in the Summer of 2018. This is required reading for every actuary.

CONCLUSIONS

It is unlikely InsurTech, big data, and big data analytics are just fads. The changing nature of the social behavior of consumers and their need and preference for technology solutions are the key reasons for the change in the platform of engagement. Industry needs consumers to thrive and the lack of regulatory infrastructure is not a showstopper. Regulators will need to develop data and model governance policies and regulatory tools to police the use and application of InsurTech technologies to prevent "unfair discrimination (McKenny, 2016, p.1)" of insurance consumers resulting from inaccurate data sources, mathematical algorithms which may mis-estimate a logical relationship between insured behaviors and insurance risks, and insurance data rating variables disallowed by regulators. Industry is wise to work expediently to develop standards of practice to police itself as a preemptive, good faith effort to aid in crafting the narrative around the regulatory control of these innovations and to work cooperatively alongside regulators to safeguard consumer protections. Consumers are influencing the changing nature of insurance transactions by demanding

Figure 1
Insurance Industry Greatest Threats



Source: A.M. Best Company. Used by Permission.

fast, cheap insurance, and a hassle-free experience. Insurers and regulators will likely need to strike a balance between regulatory supervision and industry innovation to deliver an improved level of service to consumers at competitive costs. Insurance is a profitable industry, which is strong motivation for insurers to satisfy the concerns of regulators. ■

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1 You will find the Hype Cycle at *https://www.gartner.com/newsroom/id/3798863*

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Timeline

By Robert Ellerbruch

Editor's note: This article is a departure from our usual "technical" ones. The Actuarial Speculative Fiction contest is co-sponsored by our section (along with the Actuary of the Future section, and the Technology section) because we believe that it reflects the Futurism perspective of our focus (Predictive Analytics and Futurism). This winning entry from the last contest is for your enjoyment and thought. No special technical background is necessary to read this article. If it provokes you to write a speculative fiction article of your own, we welcome it!

My acceptance onto the project team came after a contentious interview. I kept arguing with the lead student researcher regarding the implications of time travel. He was stuck on the physics of the matter whereas I kept bringing up the risks of a person being out of his/her timeline. I kept saying that just because the physics might allow it, that doesn't mean it should be done. Fortunately, the professor in charge of the team said that was exactly the attitude we needed on the team and brought me on.

The argument was not completely hypothetical for the interview. The project is an ongoing "multi-disciplinary" comprehensive investigation into the scientific and social implications of time travel. Yes, that's right, I do attend a liberal arts college.

The project is a collaboration across many departments in the college. Students cycle on and off the project each semester, and each semester one of the senior members stays on and does an honors thesis out of the research and is the lead student researcher for that semester. This spring semester the lead researcher is a physics major, hence the focus on the scientific aspect in the interview. The current professor overseeing the project (Philosophy department chair, of all people) was concerned about the science centric tilt of the team and added two new positions.

I became the team's risk analyst. Basically, that means that I will be looking for and documenting potential paradoxes (paradoxi? paradice? No, that's not definitely not right.). In short, I'll spend a semester arguing with nerds about what can FUBAR a timeline. I am uniquely qualified to argue about what can go wrong!

I should clarify, when I wrote that I would be arguing with nerds, you might have gotten the impression that I am separate from the nerds. Nothing could be farther from the truth, I'm an actuarial student and spent the previous summer in an internship counting dead people. Ok, technically I was performing a mortality study for a life insurance company. It doesn't get much nerdier than that. Yup, I'm a nerd, but just not one of the cool hard-science nerds. I'm pretty low on the nerd totem pole.

The other new position went to Jenifer. Jen transferred to the college this semester so we didn't know much about her, but she wowed the interviewers by getting into the scientific details of time travel while also raising social implications of people time traveling. The philosophy professor loved her and brought her on to cover the social, economic and political implications of humans bouncing around a timeline.

Our first team meeting was today at 3:14, its confirmed we're nerds, in the science building. Brad, the senior lead, spent most of the time talking about the experiments he wanted to run.

"We are going to combine chaos theory with our timeline research. By perturbing a chaotic system in a very minor random way, we will create new parallel timelines. It becomes a quantum model of timelines—there is a timeline with Schrodinger's cat alive and a parallel line with it dead."

"Oh dear, poor kitty," Jen piped in, "can we make sure that the cat is alive in our timeline?"

Brad rolled his eyes, "We're not going to use cats, that's just a physics teaching concept. …"

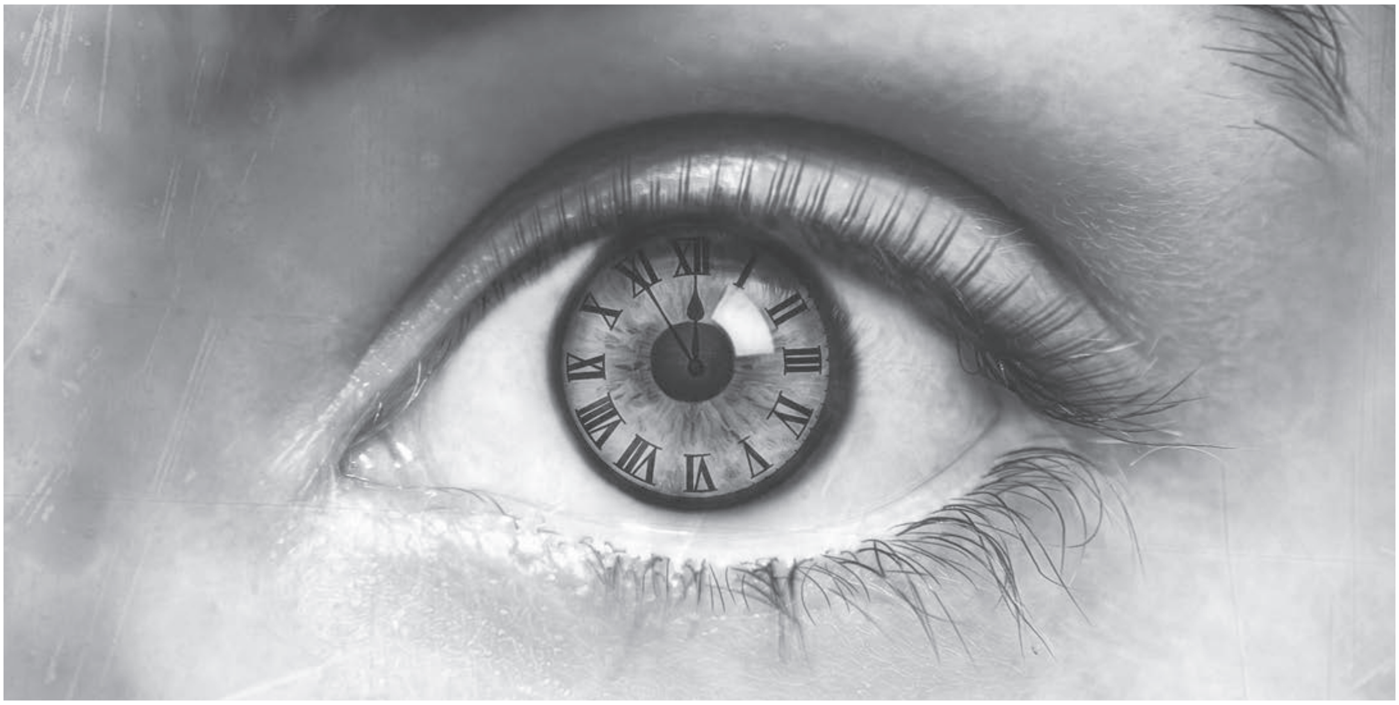
"That's a relief, society does not approve of dead cats in boxes, and, frankly, live cats are not fond of being boxed either." I chuckled as Jen trolled Brad. It will be a fun semester at this rate.

"No, that's the point of our experiment. The system will be tweaked in such a minor way that we'll be able to measure it, but it won't have any impact," Brian clarified.

At this point I could tell Jen will be a bad influence on me, as I interjected, "Wait, in a chaotic system, isn't the 'teaching concept' that a butterfly flaps its wings in China and there is a hurricane in Honduras?"

"Oh dear, poor Hondurans," Jen sighed.

"Sure, that is the theory, but there are a lot more butterflies flapping their wings than there are hurricanes, so the probability of our specific butterfly causing a hurricane is incredibly remote, right Mr. Actuary?" said Brad.



He had me there. "I'm just making sure we understand all the risks."

In that moment, Jen switched from teasing Brad to completely serious lecturer. Shaking her head, she stated, "No, the future is immutable. What has already happened will always have happened and all events caused by the past will happen. You are thinking that right now is the end of a string that keeps growing longer leaving the past trailing behind us. You think that we can change the direction of the string by our actions. That concept is incompatible with time travel. Time travel would tie that string in knots with impossibilities. No, you need to think of the timeline as a pipe, where we are in the middle of it and our past and future are already determined, if not known.

Physics itself suggests that if you had a powerful enough computer and could input ALL parameters you could model the future perfectly. Well, that much knowledge of our current situation is obviously impossible to obtain, but it all exists in our pipeline."

After picking up my jaw from the floor, I reassessed my opinion of Jen. I now could see what she showed in the interview to get her on the team. Brad was not to be deterred though.

"That is the point of a chaotic system though, you can't predict the future," he said.

"You are correct that you can't predict the future, but you shouldn't extrapolate the inability to predict the future to mean that the future is not completely determined," Jen replied.

Brad's patience clearly was at the end of his time string. "Well, I bet you are wrong."

"I bet my life that I am correct." Jen whispered, barely loud enough for me to hear.

"And that is why we are running these experiments this semester," Brian continued.

"Yes, yes it is," Jen commented. While Jen seemed sad, Brad was happy to end the meeting in agreement.

Thinking I could cheer Jen up a bit, I asked to accompany her to the cafeteria for an early dinner. We walked outside into one of those miserable January midwestern snow storms. Wrapping my insufficient coat around myself and tucking my chin as far down as possible, I grumbled about freezing my ears off because I had forgotten my hat.

Thinking that a real gentleman would offer his coat to the lady at his side, I looked over at Jen. Her coat was unzipped and blowing open in the gusty breeze. She was staring up into the sky, laughing with her mouth open while running erratically trying to catch the falling flakes. She spun around in circles like a two-year-old seeing her first snow. Finally, dizzy, she collapsed onto the ground flapping her arms and legs.

"Do you think there's enough snow to make snow angels?" She asked.

"I think all the snow angels have gone someplace warmer because its too darn cold out here for them. This is crazy, haven't you ever seen snow before?"

"No, never real snow, just pictures," she said.

"Really? Where are you from?" I asked.

"No, when." She replied.

"What, when?" I was confused.

"Why, what?" She asked smiling wryly.

"Who, why?" I could play along.

"How? Is the question you should ask." She was laughing uproariously now.

I could only shake my head. "Come on," I held out my hand to grasp her frozen hand, and pulling her up, "you're delirious from hypothermia. We need to get you out of those wet clothes."

"Ewww, don't even think about it mister. That's never happening with us."

And, thusly, I was friend-zoned before our first date.

From that inauspicious beginning, our friendship progressed with the semester. I wish I could say the same for the project. Brad and Josh (Brad's token freshman protégé), continued their experiments. The thing with running quantum experiments is that to us non-physics majors the results were nondescript.

Jen worked on a paper listing specific requirements and limitations that would be necessary for society to function in a world with time travel. She encouraged me to brainstorm what could destroy the world as we knew it. All in all, a pleasant way of passing the semester.

Brad and Jen avoided rehashing the debate on the nature of time and its flexibility, or lack thereof. But as April rolled in, and Brad's thesis and our reports were coming due, the tensions ratcheted up. It was at another 3:14 team meeting that Brad updated the group on his results to date.

"So far, the testing has not shown indications of multiple timelines being created from the perturbations. Of course, that doesn't mean that they are not created, but rather that we just can't measure them." With that he pointedly looked at Jen to see if she would take the opportunity to accept her null hypothesis. She showed remarkable restraint.

Josh was impatient and thought having negative results would hurt the project and kill any chances of a published paper. "Maybe the quantum changes we are making are too small to measure. Could we do something bigger? You know, maybe put together a chemical reaction that in one state would be stable, but in another would be highly exothermic."

We all stared at him. "You want to bomb a parallel timeline?" I had to ask.

"Not a big bomb, but enough that would change the observer allowing us to measure the impact. It would only be in that single timeline where it exploded. The alternative timeline would be perfectly fine."

I looked over at Jen, and could tell she was getting worked up. Sure enough, when she started talking, it was in her quiet and intense voice. "What if there is only one timeline? What if your bomb blows the observer right out of the time pipe? That is a lose-lose experiment. If you are right that there are multiple timelines and you can change the future, then your experiment will harm somebody's future. If the future is immutable, then whatever will happen has already been determined and your experiment will demonstrate nothing."

I wanted to defuse the bomb that was building in Jen before it harmed a poor freshman observer. "How about finding a way to test whether the future can be changed?"

Brad was ready to challenge that idea. "That would be great if we had a time traveler who came back from the future with a report of all that will happen in this so-called time pipe. But we don't have that option, and therefore Jen would argue that any future that happens, regardless of what happens, always was going to happen."

Jen nodded her head, "Congrats, you finally understand. That's why time travel is so difficult, and we need a risk analyst." She looked at me, and I suddenly felt insufficient to the task.

She continued, "Suppose, I told you that the Cubs were set to win the World Series in the seventh game, but a fan got in the way of a foul ball that was to be caught for the last out. Now this possibility is pretty crazy, so you wouldn't believe me, until I told you that the Cubs would sweep the Pirates in the NLDS, and they do. Then I say they will beat the Royals in five on a walk-off homer, and they do. Now, I have developed some street cred as a regular Nostradamus. When the Cubs lose the sixth game forcing a game seven with the Tigers, you are amazed, and also happen to be a huge Cubs fan. So, what do you do? You buy a scalped ticket, and lurk in the second row along the third base. Then, in the top of the ninth inning with two outs, a foul ball comes your way. It looks like the Cubs third baseman will get to it, but a stupid fan with a mitt is sticking his arm out. Just when it is about to go horribly wrong, you pull the fan back, the third baseman makes the catch, and "The Cubs win the Series, the Cubs win the Series!"

But, as it turns out, my future father is a huge Tigers fan. So, instead of going to bed with my future mother and conceiving future and present me, he sits in his chair drinking beer with a horrible feeling that it shouldn't have ended that way.

But now, I don't exist, and not existing, I can't tell you what will happen and you don't save the Cubs. Wait, that means that there is a celebration to be had in the marital bed, and I'm back to existing. You start to see my problem?

So, you say, my coming back in time creates a new timeline, set back by say 20 years from my original timeline. So, I am an orphan in this timeline. My parents happen to be eight- and 10-years-old, and I clearly don't have a birth certificate. You think the government has problems with illegal immigrants, well Physics is even worse. Because, not only did I come back into an existence from nothing, but I also brought a bar of gold. Now, people grow old, die and eventually decompose back into dirt, so maybe a person could just pop into existence. But a bar of gold is a valuable element and elements can't be created out of nothing. If they could, we'd be awash in gold, platinum and any other rare element our future time traveling selves could bring back. We'd have amazing technologies, we'd have knowledge, we would change the future for the better. But we are not. We're stuck on the same damn path to destruction we have been on since time immemorial.

"I know the future is immutable because we are exactly where we are right now, and this is the future from 10 minutes, 10 days, and 10 years ago.

Oh yeah, and the Cubs never win the World Series, EVER!"

Brad recovered the quickest. "You joined a time travel research project, knowing that time travel was impossible? Why bother?"

"No, you don't get it, I'm not saying it is impossible. I am saying all time travel that will happen has already happened, and the results of that time travel are exactly what you see in front of you. A traveler can't change the future, just like you can't change the past, all a traveler can do is play her role the same as she always has and always will."

It was time to defuse this meeting, so I excused Jen and myself. We left the building for our customary walk to the cafeteria. The sun beat down on us from a clear blue sky. Jen turned her face up to the sky, soaking in the spring rays.

"Its beautiful you know," she said as she took off her shoes and socks to walk in the grass barefoot. "You don't realize how amazing it is unless you've been without. That's your problem now."

I laughed at that. "It was a bad winter sure, but you seemed to like the snow the first time you saw it!"

Ensconced in her own world, she didn't pay any attention to me, but just continued on reflecting. "The seasons, they're great. The tulips coming up, cherry and crab apple trees flowering." She breathed deeply. "You know, I was wondering if I would be allergic. I almost wish I was allergic."

We walked through the quad and stopped on top of a small bridge over a man-made pond with a fountain bubbling water down a rock wall into the pond. Colorful Koi swam lazily below us hoping for some food.

Jen started laughing, "There you go, they're here for you." She was pointing at a bunch of geese and other birds pecking around the grass.

"What?" I asked.

"It's a pair a ducks, you should add them to your report."

"Um, I don't think a bad pun is appropriate for a serious academic paper."

"Well, you should at least put a picture of them on the cover page. Future readers will appreciate it I'm sure."

When Jen was in one of her reflective happy go-lucky moods, it was always fun. In order to encourage it, I just had to ask, "So, Miss futurist historian, what do you see in the cards for us, certainly you weren't serious about the Cubs never winning a World Series!"

"Sorry about that, it was cruel to break it to you like that."

"How do you even know I am a Cubs fan?" I had been since first seeing them with my mother in the friendly confines of Wrigley for my first ball game.

"You have that long-suffering wounded look."

"Actually, that look only started when you 'Ewwed' at the prospect of us getting naked together, I was perfectly happy before that."

"Trust me, you'll thank me for that."

"Hmph, not sure about that. Do you have any other cheerful insights, my fully dressed oracle?"

She thought a bit, "Well, I guess it won't hurt to tell you now. The good news is I foresee you actually seeing a woman naked in your future, and you will be very happy about it."

"Wow, way to go out on a limb there."

"Let's see, there's more bad news than good I'm afraid. This won't be around for very long." She gestured widely.

"What, the campus?"

"The park, the grass, pond, flowers. Students sunbathing. Depletion of the ozone will make being in the sun a thing of the past. Global warming and extreme temps take care of much of the rest. The Cubs will only have about 15 years of additional futility before baseball becomes a thing of the past altogether. Humanity was increasingly forced into the protected indoors. They can't afford to spend limited natural resources on luxuries." As intelligent as she was, Jen had major problems keeping her tenses consistent.

"Wow, you're just Debbie Downer all of a sudden."

"Its okay, people adapt. Science finds ways, not soon enough to prevent, but in time to facilitate survival. Every generation has always told the next generation about how much better it was back in their day. Youth, not knowing anything different, shrug it off as reminiscing old folk and continue on with their life."

"Maybe I shouldn't have asked you."

"Oh, but for you, I see good things in your immediate future. I see a cold beer, good company, and dancing, definitely some awkward actuary dancing."

I had to laugh; I don't dance, but I did have the awkward part of the prediction nailed. "I question your magic 8 ball, but it sounds like we're headed to Barr's Bar rather than the cafeteria."

"Not 'we' Kemosabe, I'm staying here and lying in the sun!"

And you know, Jen was right. At Barr's Bar, I had a cold beer, or three, met some friends, and had a great conversation with Rhonda. I'm embarrassed to admit there was even some awkward actuary dancing. I initially objected, but even I know you don't let a pretty girl go on the dance floor alone if you want to continue your night with her.

Two weeks later after our last final exam, and finally handing in our respective papers on the project, Jen and I were again walking across the quad. Rain clouds threatened a spring storm. The heavy air seemed to weigh on Jen as we walked.

"So, now that we are done with the semester, what are your plans, Ms. Futurist?" I liked to kid her about her soothsaying since the time she successfully predicted my successful evening with Rhonda. But, as much as I prodded, that had been the last of her predictions.

"I don't know. The future may be immutable, but after tonight my future is unknown," she said.

"Well, you'll be back for fall semester right?"

"No, I will be moving on."

I was surprised how much that hurt me. I felt like we had really connected this past semester. I had hoped that there would be a future for us, even if it was as fully-clothed friends. "I'm sad to hear that Jen. I hardly know you, and now you're moving on without me? It seems like you know more about me, my past and my future, than I know myself. Yet, I know nothing about you."

"Unfortunately, you never could know me as much as we both would have liked. I'm happy we had this semester."

"So, tell me something about yourself, are you going back to family now?"

"No, I had to leave my mother to come here, and I don't think I can go back to her. I hadn't known my father. He died during my birth."

"What? That doesn't make any sense. Childbirth isn't generally risky for the father."

"We were driving to the hospital, my mother was in labor and worried we wouldn't make it. The weather is not good, and we are t-boned by another car. The paramedics are able to treat my mother and assist in delivering me, but, well, I'm sorry."

She looked at me with tears running down her cheeks as fat drops of rain fell. We hugged. She whispered, "What will be, has been already. Now, go have yourself a great date. I heard that the third date is an important one."

Jenifer turned around, and as the rain fell, I watched my daughter walk away. ■

Robert Ellerbruch, FSA, MAAA, is a retired life actuary working on determining the rest of his timeline. He can be reached at *rellerbruc@aol.com.*

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