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How Significant Is Statistical Significance?

By Rosmery Cruz

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"Back When I Was an Actuary ..."

By Dave Snell

Have you ever heard the joke about the doctor and the plumber? A famous doctor was hosting a party at his house, and 30 minutes before the first guests were to arrive, he discovered to his horror that the bathrooms had all backed up and were unusable. Panicked, he called an emergency plumbing service. Just 10 minutes later, a plumber arrived, took one quick look at the situation and fixed the problem in five minutes. She then presented the surgeon with a bill for $350.

The doctor was amazed. "Are you kidding me? I am a physician, and even I don't make $350 for five minutes' work." The plumber smiled and said, "I know just how you feel. Back when I was a physician, I didn't make that much either."

My point here is that artificial intelligence (AI) and machine learning are changing the relative values of many professions. Initially, it was thought that telemarketers and others with routine tasks were the targets for replacement by AI. In fact, a 2013 study at Oxford University listed 702 occupations and showed telemarketers and basic insurance underwriters as having a 99 percent likelihood of being replaced by AI automation, while doctors, actuaries and lawyers were considered practically immune from such replacement.[1] Yet on May 12, 2016, *Fortune* magazine announced: "Ross, the first artificially intelligent attorney, just got a job. Global law firm Baker & Hostetler, one of the nation's largest, recently announced that it has hired a robot lawyer created by ROSS Intelligence, Futurism reports. Ross will be employed in the law firm's bankruptcy practice which currently employs close to 50 lawyers."[2] Oh, and in case you need similar capabilities and can't afford a staff of attorneys, you can rent Ross for $125 per month.[3]

Likewise, IBM's Watson, and other AI programs, are being employed every day to form diagnostic opinions for doctors for several diseases. Earlier this year, for diabetes, it was announced that "a team of Australian-Brazilian researchers led by RMIT University have developed an image-processing algorithm that can automatically detect one of the key signs of the disease, fluid on the retina, with an accuracy rate of 98%."[4]

Yes, telemarketers are still likely to be replaced by AI. But a bigger return on AI investment is to replace any person who basically just looks at lots of data and makes a judgment call—for high compensation. A doctor looks at your lab reports, asks you questions for perhaps 15 minutes a year and then draws upon a knowledge base of perhaps hundreds or even thousands of patients. An AI program can read lab reports, streaming data from your wearable or embeddable monitors, and thousands of articles on interactions with your medications and your genetics and draw upon a database of millions of patients. The AI can assimilate facts faster and from more sources. Soon it will make better-informed diagnostic summaries and make tailored recommendations for you.

Yet not all professions are in danger of near-term replacement by AI. Many futurists (including me) believe that nurses will be around decades after most surgeons have been replaced, because they must use cross-functional skills. They are the professionals personally caring for the sick. They must exhibit compassionate interaction with the patient about to get a needle injection, help with physical movement, decide when the sheets must be changed and administer medications—while also providing comforting conversation. Likewise, plumbers—and several other tradespeople—are going to be tough to automate, as they must combine physical dexterity, code requirements and diagnostic knowledge skills in such varied environments as residences and businesses of all types. A robot could not depend upon a sterile operating room and standardized equipment.

Now let’s take an honest look at actuaries. Where do we fit in the spectrum of potential replacement by AI? I hear at so many actuarial meetings that we possess business knowledge that cannot be replicated by AI. Yet in the past few years, various models are being developed that show what we claim as business knowledge might also be unconscious bias. In life insurance, the biggest three usable factors on longevity have been thought to be age, smoker status and gender. AI models of hundreds of potential features and interactions now show that various credit and lifestyle parameters can be combined to form new metrics, such as the TransUnion TrueRisk Life[5] score, that may be more impactful predictors of longevity and persistency than even smoker status. Our business knowledge and experience is certainly an asset, but we must realize that it also comes with the baggage of bias based upon it. An AI model has no such inherent bias (unless preprogrammed). No human matches (experience) were input as part of the training for Alpha Zero, and it became the master of chess, Go and shogi.[6] That vast human experience can sometimes be an obstacle to more innovative thinking.

All [the articles in this issue] contribute to an awareness of the need to broaden our thinking and consider new skill sets.

If all you do is assimilate data on mortality and morbidity, or reserve needs, and determine a best-estimate premium for the combination, why would you think that could not be automated via AI machine learning? On the other hand, if you are among the group of actuaries who can embrace the predictive analytics and AI machine learning tools, and also can explain the financial risk concepts and consequences for your external clients (or your internal management) in understandable terms and can guide them to better paths, you probably need not fear automation for a long time.

One reason actuaries still have not been encountering much danger yet is because only 35,000 or so SOA members is still a small target for replacement versus over a million U.S. doctors[7] and even more lawyers.[8] But it is time to rethink your skill set.

This issue of our newsletter has fewer articles than usual, but some are longer than usual, and they all contribute to an awareness of the need to broaden our thinking and consider new skill sets:

- In “How Significant Is Statistical Significance?” Rosmery Cruz discusses the p-value that we often use and perhaps overuse to determine significance. Sometimes we place too much reliance upon canned metrics and lose the ability to notice when something is mathematically sound but not sensible. Rosmery gives three simple examples that require no complicated mathematics to follow yet provide a basis for some deep thought about statistical significance versus substantive significance.

- Next, Jeff Heaton gives us new insights into applications of a relatively recent and amazing type of neural network in his article “Semi-Supervised Learning with Generative Adversarial Networks” (GANs). By now, you likely have heard of GANs being used to create original artwork that fits into a specific genre, but the question I get most about GANs from actuaries is “how can they be useful for insurance?” Jeff provides a tantalizing example of generating fake (but usable for underwriting and actuarial studies) medical records. This is part one of a two-part set of articles. He also provides a link to a video in which he shows how to get started with GANs using the free Google CoLab facility.

- Moving along from statistics, numbers and code to predictions from humans, Xiaojie (Jane) Wang and I interviewed two visionaries involved in start-up FinTech. In the interview article “Startup Heads Share Visions of the Future of Insurance,” they share some interesting insights. One notable quote: “As a data scientist or a modeler, your results are more powerful and useful, when you can articulate what it means to a wider organization. Reach out to the underwriter or the client manager as to why your models predict a certain behavior for a certain client demographic.” This is completely in harmony with our theme this issue.

- The results are out for the 2019 Actuarial Speculative Fiction contest, and the winner for our section was “We All Have a Green Heart” by Anna Bearrood. This story is such a great example of how actuaries can transform themselves and others to advance the profession and the world that we have included it here in its entirety. Yes, it is long, but it is well worth reading. As a profession, we have been politically complacent for too long. We have the skills to bring about positive change. In doing this, we can elevate the public awareness and appreciation of actuaries. Congratulations to Anna for a very upbeat and well-researched story!

- Finally, I have written an article, “Come Visit Philadelphia This September,” about why you ought to consider attending this year's Predictive Analytics Symposium (September 19–20). We are the section sponsoring this meeting of various experts, novices, managers and just plain kindred spirits among the actuarial community. It is an educational and networking bargain. I hope to see you there!

I started this editorial with some pessimistic scenarios about the future for doctors, lawyers and actuaries. But if you read through the various articles in this issue, you will see that our future does not have to be gloomy. It could be great. Some doctors, some lawyers and hopefully many actuaries can start enhancing their skills now (in predictive analytics, emotional intelligence and presentation abilities) and have very productive careers—perhaps even more meaningful ones than in past times. And we might even initiate a collaborative solution to the global warming issue!

Enjoy our issue, and please continue to give us feedback on what you like and what you want to see more of in future issues. ■

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How Significant Is Statistical Significance?

By Rosmery Cruz

Statistical significance is widely used. Many researchers use the concept to confirm their theories. Others use it for data exploration, trying to determine what variables are "important" in their particular area of study. There is growing skepticism about the use of this methodology. Some suggest it does not tell us what we want to know (Ioannidis, 2019). Others suggest that statistical significance has set back scientific research in general (Wassertein and Lazar, 2016). Many advocate that we should stop using p-values all together (McShane, Gal, Gelman, et al., 2019). This article explores the problems with statistical significance and suggests a commonly accepted pathway forward.

WHY IS STATISTICAL SIGNIFICANCE USED?

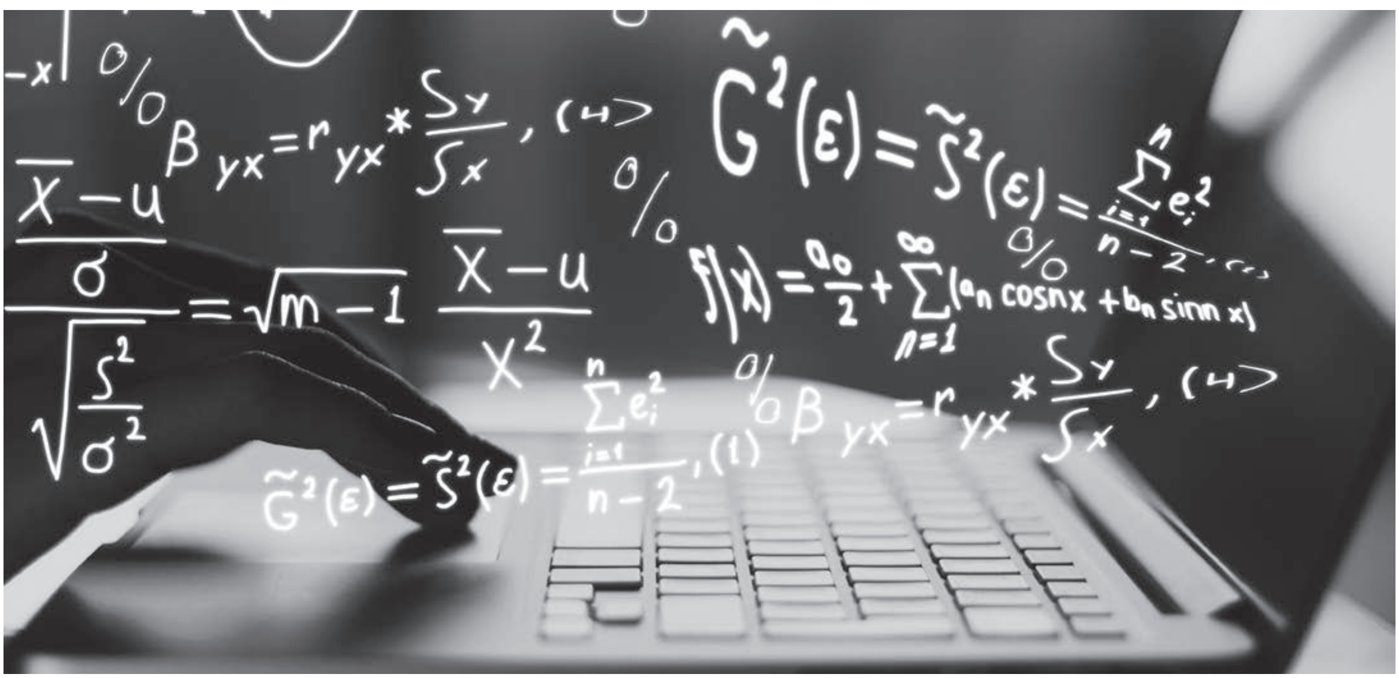
Statistical significance is designed to adjudicate between competing hypotheses. Specifically, this test evaluates an alternative hypothesis in the context of a null hypothesis. Let's say we want to know some effect B, which represents the degree to which income affects mortality. The null hypothesis suggests that income does not affect mortality. Thus, B equals zero. The alternative hypothesis states that B does not equal zero, meaning that income affects mortality (either positive or negative). Tests of statistical significance assume that the null hypothesis is true and estimate the probability of observing the sample data. It's important to note that while not discussed here, statistical significance in observational studies does not imply causation of any kind.

STATISTICAL SIGNIFICANCE DOES NOT EQUATE SUBSTANTIVE SIGNIFICANCE

Statistical significance does not represent substantive significance. Notably missing from the definition above is any discussion about the degree to which an effect is important. This is because statistical significance does not tell us if we have discovered an important effect. Instead, these tests tell us whether or not our confidence interval (at whatever chosen level) contains zero. This means that our effect estimates can be small and large, with variable uncertainty, and retain statistical significance. As a result, two important questions go unanswered. First, what is the size of the effect? (Does it matter?) Second, how certain are we about the size of the effect?

AN EXAMPLE

Returning to the example above, let's again try to determine the effect of income on mortality (B). Assume that we have



conducted three observational studies to understand this relationship. Each study has returned an estimate of B, and in each case, the effect is statistically significant. In a total vacuum, we might want to conclude that each study indicates that income affects mortality. But we know that statistical significance omits key information, so we would be left wondering if the effect was important.

Scholars have suggested graphically illustrating estimated effects from quantitative studies (Gelman and Paradoe, 2007). In general, these graphs should demonstrate several aspects of the results. First, they should display the effect of interest (the average effect). For example, we might plot the coefficients from a regression model (when interactions are absent). Second, these figures should illustrate the degree to which we are uncertain about the presented estimates. For instance, we could plot confidence intervals in addition to coefficient estimates from a regression model. With this information, an analyst can better understand the degree to which a variable affects an outcome of interest.

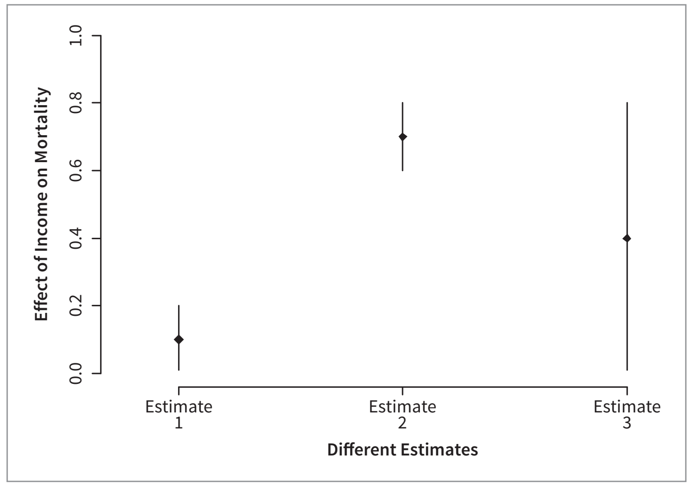
Figure 1 demonstrates that three statistically significant findings can represent different substantively meaningful findings. Returning to our previous example, Figure 1 displays three estimates of the effect of income on mortality, with 90 percent confidence intervals. As noted previously, each result is statistically significant at the 5 percent level, because each confidence interval does not contain zero.

What do these results suggest about the effect of income on mortality? Estimate 1 suggests that the effect of income on mortality is small with little variance. In this case, actuaries may choose to examine other variables to understand mortality better. Estimate 2 suggests that the effect of income is large, with a small confidence interval. In this scenario, income is highly relevant to mortality, and we might consider developing products around this variable. Estimate 3, on the other hand, suggests that the effect could be large but that we are highly uncertain. Put another way, the confidence interval includes values near zero. This result suggests that if we were to repeat this experiment, we might find that there is little correlation between income and mortality. The substantive conclusion here is that the business needs to do more research to understand this effect better.

CONCLUSION

The previous example provides a path for analysts to understand how variables of interest affect mortality. Other ways analysts can check the value of their findings is by looking at measures of model fit (if a model is being used). For example, if an analyst is adding income to a model of mortality, they could show that

Figure 1
Three Estimates of the Effect of Income on Mortality



the additional variable reduces the out-of-sample error for the model. This model fit can be estimated using holdout data or leveraging a fit statistic like AIC or BIC.

This article illustrates why statistical significance alone should not be used to understand how variables affect the outcomes of interest. Additionally, this paper shows how graphical representations of the effects of interest can improve our understandings of the relationships found in our data. Specifically, visualizations help the analyst understand the size of the effect as well as the uncertainty around that estimate. ■

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Semi-Supervised Learning With Generative Adversarial Networks

By Jeff Heaton

In the world of machine learning, supervised and unsupervised are the two premier methodologies usually discussed. Most problems, and the models used to deal with them, are either classified as supervised or unsupervised. However, there are other types of models beyond supervised and unsupervised. Models that support semi-supervised and reinforcement learning are two model types that have lately been gaining considerable traction. In this two-part article series, we will look at semi-supervised learning. This article will begin by introducing semi-supervised learning and the generative adversarial network (GAN). The GAN, which is usually shown in conjunction with image rendering, will be demonstrated to have insurance industry applications. The second article will provide a more technical implementation of a semi-supervised GAN, using Keras and TensorFlow, for health care data.

AN INTRODUCTION TO THE GENERATIVE ADVERSARIAL NETWORKS

GANs have received a great deal of publicity lately for their ability to generate realistic human faces. The Python package called StyleGAN, available from nVidia, makes for a great introduction to face generation with GANs. Setting up an environment to run StyleGAN can be challenging. It requires a current nVidia GPU, along with a Linux operating system. I suggest using the free Google CoLab (free) for GAN experimentation. Google also provides a free K80 GPU, which is more than sufficient to begin experimenting with GANs. I provide a video that contains detailed instructions for setting up CoLab with GANs.

Figure 1 shows a face that I generated using nVidia StyleGAN. It looks quite realistic. At first glance anyway. If you know what to look for, you can probably spot a fake human face. Does anything about Figure 1 look out of the ordinary?

Any sort of accessory is usually one of the first giveaways. In this case, the earrings are a dead giveaway. Ears are also often nonsymmetrical. Often a GAN-generated face will have two completely different earrings and often two very differently shaped ears. The background is usually a giveaway as well. The background of a GAN-generated image is typically surreal looking. It looks natural, but you are never quite sure what you are looking at. Linear projections that begin on one side of the face often do not align to what is behind the other side. For this image, the background is not that surreal, but I am also not entirely sure what I would classify the background as either. There are other common giveaways as well, particularly if the image is high enough resolution.

Figure 1
Real or Fake?

A GAN accomplishes this generative capability by learning the underlying distributions of source data. The source data does not need to be images. GANs can learn from nearly any sort of data. Consider a GAN that might be trained on medical data. The GAN would quickly learn the distributions of the input data. Input columns such as gender, blood pressure, height, weight, age and even various lab tests could all have their distributions learned by the GAN. With these distributions learned, the GAN could now learn to generate fake medical records just like it creates fake images. If portraits were available together with medical data, the GAN could theoretically learn to generate the medical records behind the impostor faces that the GAN is generating.

However, the GAN does not just learn the individual distributions of the source data. The GAN also learns the conditional distributions and other correlations among the input features. This is why the faces appear so realistic. The GAN matches human face characteristics in ways that we are used to perceiving in real humans. The GAN would perform similarly when attempting to generate impostor medical records. Correlations among age and blood pressure, for example, would be considered. This would add to the realism of fake medical records.

How Do GANs Work?

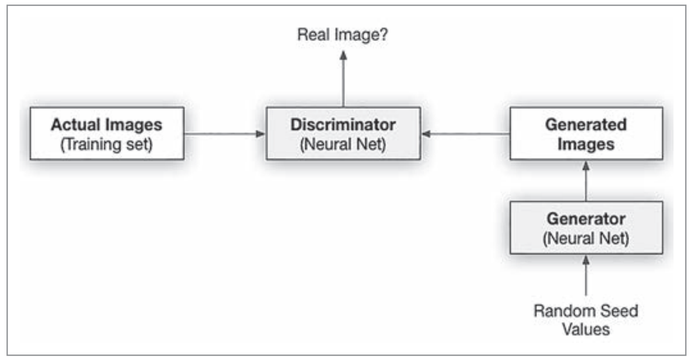
Though most coverage of GANs in the media has been for image recognition, there is nothing about a GAN that directly ties it to image processing. Likewise, though GANs are most often demonstrated with deep learning, there is nothing that ties a GAN to neural networks as the underlying model. When a GAN is used for computer image processing, it is most often used with a convolutional neural network (CNN). This makes a great deal of sense, because CNNs are among the most state-of-the-art models for image processing.

The name generative adversarial network describes the algorithm well. Training of a GAN is essentially an arms race between two neural networks. The GAN algorithm is a zero-sum noncooperative game.

- **Discriminator neural network.** Given an input image, predict the probability that the image is real.
- **Generator neural network.** Given an input random vector, generate a realistic-looking image that will fool the discriminator.

The beauty of this approach is that it is unsupervised. Source images are needed, but they do not need to be labeled in any way. No human intervention is needed. If a human were needed to rate each of the generated images, it would take a considerable amount of time to train such a network. Rather, the two neural networks are learning from each other. The discriminator learns to discriminate better by evaluating what the generator produces. Likewise, the generator also ups its game trying to fool the discriminator. The process is summarized in Figure 2.

Figure 2
Generative Adversarial Network (GAN)



Once training is complete, the discriminator is usually discarded, as you now have a generator that can generate data that is limited only by the number of random seed vectors that you are willing to generate.

GANs FOR SEMI-SUPERVISED LEARNING

When I first saw GAN technology, I was captivated by the amazingly realistic-looking images that they produced. However, I did not see a great deal of practical use to my job as a data scientist working for a life reinsurer. Ultimately, once I saw their application to semi-supervised learning, I began to evaluate this new technology.

Semi-supervised is useful when your data are only partially labeled. Maybe you have a large number of medical records but underwriting decisions or mortality experience on a small number. For mortality experience, semi-supervised would be cases where you do not know how long the individual ultimately lived. Instances where some individuals are still alive and only a handful have died would not be considered semi-supervised, as you do not have labels for all the data. Also, such situations might better lend themselves to survivor modeling.

Semi-supervised learning is very biologically plausible. Children see a wide number of human beings in their early childhood. Very young children see these samples of humans well before they know ages and genders. This foundational knowledge is very useful when they begin to receive labels and learn to discern ages and genders with increasing accuracy. This is somewhat how GANs are applied to semi-supervised learning.

This article presented GANs and showed how they can be extended to implement semi-supervised learning.

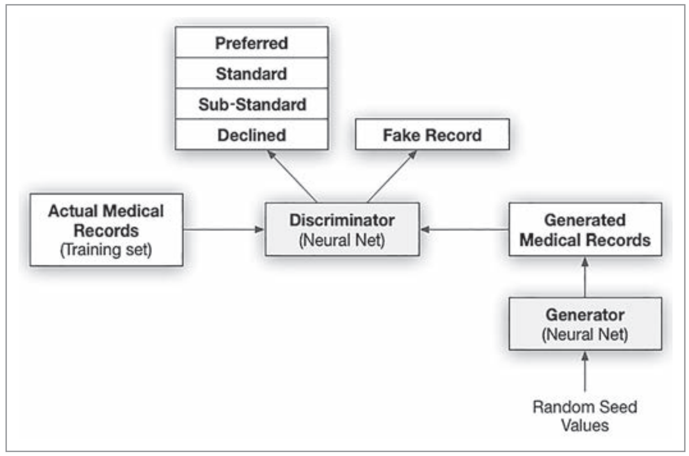
Traditionally, GANs produce a useful generator, leaving a discriminator that is discarded. Semi-supervised GANs flip this entirely. The generator is used only to train the best possible discriminator that will be the ultimate model artifact from the training exercise. The discriminator for a semi-supervised GAN will not simply classify between real or fake. The semi-supervised GAN will classify into a set number of classes plus an additional class for fake records. This is used to train the generator to produce more likely fake data. However, in the process, the discriminator is getting very good at not only classifying but also detecting fake records. Once training is done, the fake record classification can be used as an anomaly detection mechanism should anything be classified as fake in production. This process, for an insurance underwriting system, is shown in Figure 3.

Figure 1 shows how to perform semi-supervised training for classification. For regression, the neural network would simply have two outputs. The first output neuron would be the regression prediction. The second output neuron would present the probability that the input data was fake.

NEXT STEPS

This article presented GANs and showed how they can be extended to implement semi-supervised learning, which can be extremely beneficial when your dataset is only partially labeled.

Figure 3
Semi-Supervised Learning



The next article in this two-part series will show a technical implementation using Keras. This will show how to perform predictions of partially labeled medical data. ■

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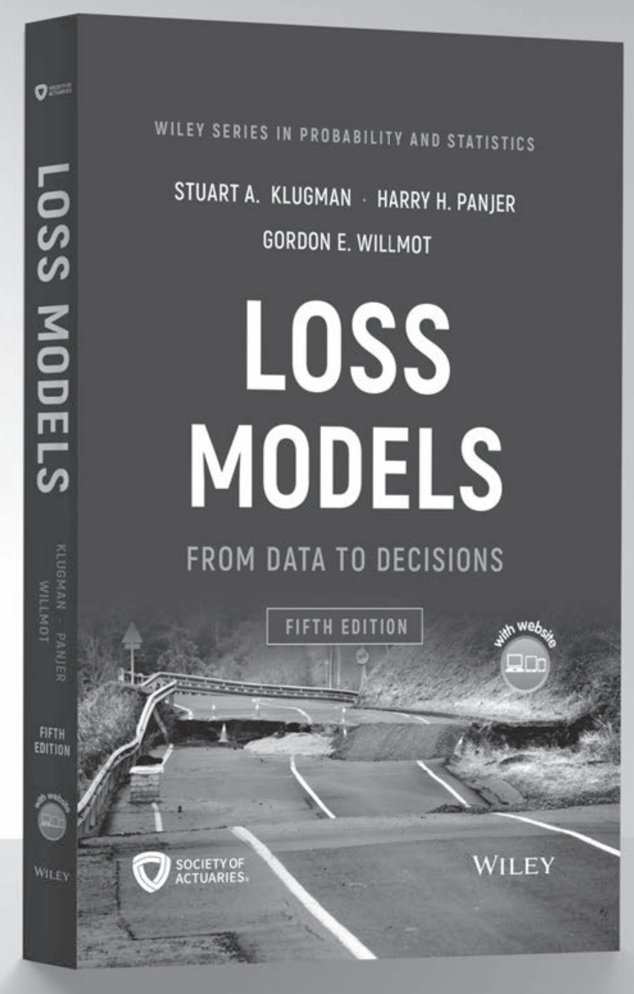
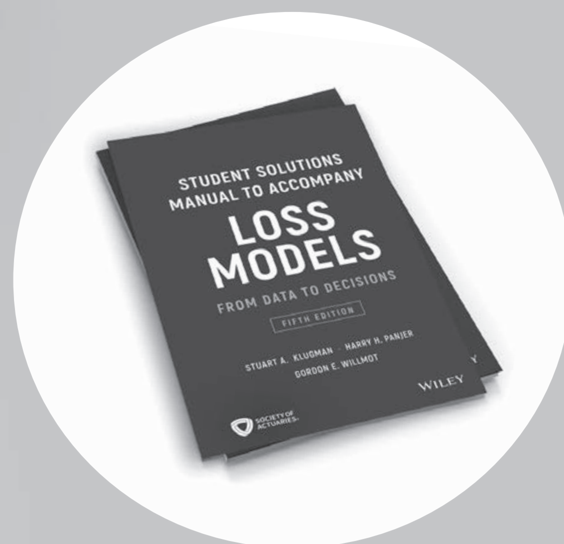
Loss Models:

From Data to Decisions, Fifth Edition

Stuart A. Klugman, Harry H. Panjer, Gordon E. Willmot





The accompanying **Solutions Manual** provides detailed solutions to the book's many exercises, some of which are drawn from past SOA examinations.

This edition provides updated material to align with the **2018 SOA curriculum changes** that introduced the Short-Term and Long-Term Actuarial Mathematics exams (STAM and LTAM). The book focuses on modeling the loss process using parametric, nonparametric, Bayesian and credibility techniques. Loss processes include claim amounts, claim frequencies, time to decrement (single and multiple), and the collective risk model. While organized to follow the learning objectives of these exams, the book remains a valuable resource for any actuary engaged in building models for uncertain future events.

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Startup Heads Share Visions of the Future of Insurance

By Xiaojie (Jane) Wang and Dave Snell

In our May 2019 issue of the *Predictive Analytics and Futurism* newsletter, we published a summary of an interview with two industry leaders from global reinsurance companies. As a reminder, you can listen to that entire interview (that is, our questions—plus many from the audience) at *http://bit.ly/2Pv3bPE*. In this issue, we asked some of the same questions of thought leaders at two startups.

Dr. Renu Ann Joseph is CEO and founder of Luminant Analytics (*https://www.luminantanalytics.com/*), which offers "targeted analytics for the insurance industry," and Ben Hsieh is the director of Product Development at Bestow (*www.hellobestow.com*), which is "on a mission to make term life insurance simpler and more human."

Xiaojie and Dave: How do you optimize an Insurtech strategy, such as predictive analytics?

Renu: To deploy the full potential of predictive analytics, first, business units within an insurer need to be in sync. Pricing should be in sync with underwriting and reserving, which in turn, talks to claims management and customer engagement. Our value proposition is the unique ability to effectively convert external data analytics and predictive models into an insurer's current risk management processes in an easily digestible manner. Then as more of the business units start syncing, our efforts start generating transformational multiplier effects because we integrate key external environment changes to an insurer's book, helping them not to get caught out on unforeseen market changes.

Ben: Our strategy begins with continuously monitoring, assessing and modeling the data interactions across marketing, customer experience, underwriting, actuarial, accounting and administration platforms. Tracking all data flows and interactions throughout our full stack technology platform helps us prioritize and organize how we deploy additions and modifications to model inputs and parameters.

Xiaojie and Dave: What are the most important lessons you have learned from the implementation of predictive analytics strategy and projects in your organization?

Renu: As a data scientist or a modeler, your results are more powerful and useful, when you can articulate what it means to a wider organization. For example, reach out to the underwriter/claims manager, who is not a typical recipient of such information, as to why your models predict a certain behavior for a certain client demographic.

Ben: One key lesson is the strategic allocation of resources to the most fundamental platform elements. Learning how to quantify and assess impacts to our technology stack helps us organize and prioritize what we wish to accomplish.

Another lesson is ensuring we understand the strengths and limitations of the vendor predictive model outputs we incorporate into our own model as inputs. We continue to learn how vendor models are being trained and how that calibrates to our customer demographics.

As a data scientist or a modeler, your results are more powerful and useful, when you can articulate what it means to a wider organization.

Xiaojie and Dave: What are some of the new types of data we are encountering, and what can we expect in the near future?

Renu: There is constant bombardment of "big data" that will continue to grow—real-time traffic data from satellites, drones, telematics devices. Probably the next big wave is data coming from IoT [internet of things] devices. The challenge is to filter signals from the massive volumes of data that it will generate.

Ben: Testing and utilizing datasets that are relevant to mortality but not historically used is necessary to supplement our experience data and create a competitive advantage. The types of data being evaluated include behavioral (how people behave during underwriting), health and socioeconomic data points.

Xiaojie and Dave: The infrastructure can be daunting. Does size determine success in this new environment?

Renu: No, size does not. The past few years have seen the emergence of many cloud-based server options. So storing and managing data is not a problem. However, it is the agility of current systems that matters. Legacy systems, across insurers, are not set up for change in terms—mindset, processes, attitude.

Ben: No. Quality of data inputs, model architecture and talent are key to success in this environment. The unification of marketing and underwriting data will be highly impactful to future product and underwriting development. Despite significant progress made over the last five to 10 years, we are still very early in the development of predictive analytics within the life insurance industry.

Xiaojie and Dave: What advice do you want to share to keep an insurance company from becoming obsolete?

Renu: 1. Product innovation and new players are moving in at a fast pace. If incumbents think that the way they operated before worked and continue that, they are wrong. The marketplace is changing, and it is a force they cannot stop. 2. Listen to your customer more than ever. Insurance has a bad reputation, and with the younger generation having different value systems than the current, customer engagement and retention are important more than ever. 3. Leverage data within your organization well. Break the silos, and this will make your systems more receptive for new technologies.

Xiaojie and Dave: What is your vision of future insurance?

Renu: 1. Leaner and transparent wordings. 2. Dynamic pricing. 3. Fully automated processes for claims management, underwriting, contract reviews, pricing and reserving functions. These departments can be reduced considerably in the next decade along with improvements in output quality with the right use of the right technology.

Ben: We are working to build a more efficient market matching risk and price—getting the best products to the right people. There is more innovation happening in this space than at any time in its history.

Xiaojie and Dave: What have you learned from old players or new players that could benefit your organization?

Renu: 1. You don't need a large team to achieve amazing results. You need a smart, compact team with laser-sharp focus. 2. Multidisciplinary teams are a necessity for insurance to innovate. 3. Innovation is successful only when companies adopt the changes. The biggest impediment to that is mindset change. Hire the right people, and constantly train and motivate them.

Ben: We value the tremendous amount of wisdom built up over decades of experience. Then we build on that with better models, correlated data and challenging historical paradigms to create a more holistic approach to pricing risk. In any regard, change is happening faster than most people expect, and we expect that to accelerate. ■

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We All Have a Green Heart

By Anna Bearrood

Editor's note: This story won the Predictive Analytics and Futurism Section prize for most novel prediction forming the basis for the narrative in the 2019 Actuarial Speculative Fiction contest, which our section co-sponsors every two years. You can read all the contest entries at https://www.soa.org/sections/2019-speculative-fiction-contest/.

"We are engaged in a contest for the most *interesting* documentary about the reversal of climate change, and she wants us to interview an *actuary*?" James inquired incredulously as we left our boss's office with a large camera on a tripod leaning heavily on his shoulder.

"They can't all be socially awkward, can they?" Lisa asked, twirling reflectors nervously in her hands.

"Does it matter? I've heard they don't like social interaction," James insisted. "And we're supposed to put one in front of a camera for millions to see!"

I reached my desk and relieved my arms of audio equipment. A newspaper had crushed the haphazard notes strewn across my work area, its headline screaming "CLIMATE CHANGE HAS BEEN REVERSED." I straightened and looked at my two colleagues. "This all started with an insurance company," I stated, pointing at the newspaper. "Now, I know it may not seem very exciting, but I think it could be a unique and efficient way to explain how it all began, don't you think? The other teams might be using celebrities or miracles or fluffy animals or whatever they can think of, but we're going to get to the place where it all started."

James raised an eyebrow. "You mean a cubicle?"

"Um … exactly!" I grabbed my purse and phone. "Let's get our stuff in bags and get on the train. This is going to be great! We just … We just have to find the right actuary!"

Following the high-speed train ride from New York to Minneapolis, a few calls, a brainstorming session and an overnight stay in a hotel, my team and I hopped on the subway in the direction of Green Heart Life Insurance Company for the first day of filming. Green Heart was located in a net-zero building downtown, surrounded by bike paths, walking streets and green spaces.

My team set up in a decent-sized conference room, and the first potential interviewee was a corporate actuary.

"Hello, Mr. Beckman. Thank you for talking to us," I told him as he shifted in his chair across the table. "My cameraman, James, will position himself here, but I want you to look at me while you're answering the questions, not into the camera. My assistant, Lisa, will control the lighting; don't mind her. Are you comfortable?"

Mr. Beckman looked at anything but my eyes and nodded.

"All right, please look at me when you are answering the questions. I'll just ask you one question as a test, and then we will contact you again if we want you to be more involved in our project. The first question is: Why did an insurance company get involved in the climate change revolution? What's in it for you?"

"In the simplest terms," he began, staring at the table, "insurance companies and customers have the same goal: to have policyholders live longer. Let's take a simple whole life insurance contract. The customer or policyholder pays the insurance company a certain amount of money—called a premium—every year until they die. When the policyholder dies, the insurance company pays a lump sum to the policyholder's beneficiary—spouse, child, etc. So the longer the policyholder lives, the more premiums they will pay to the insurance company to offset the cost of paying the lump sum at death. Insurance companies want the policyholders to live longer so that they will receive more money. And policyholders? Well, policyholders also want to live longer because everyone wants to live longer. Same goal!"

After Mr. Beckman had left, I shrugged at my crew. "Great answer, zero eye contact."

The next actuary worked in life insurance.

"We've been able to lower UEP amounts for WL, UL, VUL, everything, since the U.S. LE is so much longer. The SOA and AAA worked together on the studies we needed. The NAIC's SVL within the VM uses PBR, so CRVM and CARVM were adjusted accordingly. Once the CSO table was updated, we were good to go! LT9 is our cheapest product yet!"

I shook my head.

A director in the annuities area named Mr. Phillips was the next interviewee.

"It's called nudging. You track a certain aspect of someone's life as a basis for the amount of premium they pay, and they will improve that aspect of their life. For example, back when people drove cars …" Everyone laughed. "An insurance company could have the policyholder place a monitor in their car to track how they drive. The better they drove, the better their premium, so they drove better! It's the same idea with our Green Heart program. We've since renamed our company to match the program. We encourage climate-saving and health-saving behaviors that will lengthen the policyholder's lifespan. Then for life insurance, we are able to charge lower premiums because people are expected to live longer. Thus, policyholders are nudged toward that beneficial behavior.

"The life insurance side is where most of the creative process took place, but I can also explain how my area—annuities—benefits from longer life expectancies. I'm going to need a break though. Being around people and cameras drains my energy."

"You've been here for two minutes."

The actuary nodded. "Yes, that's about my limit."

I put my head in my hands.

The next candidate was another life actuary, this time a cheery woman in her 30s with wavy red hair and a brilliant smile. She greeted the three of us with a direct handshake and eye contact that was neither flickering nor unwavering. She sat down, nodded at the directions, and looked at me when I asked the first question.

"Hello, can you give us your name and what you do here at Green Heart?" I felt good about this one, so I approached the questions not as a test but rather as if I was doing the real thing.

"My name is Brooke Piper, and I work in life insurance to create and price new products."

"What is it that makes something like life insurance the perfect vehicle for helping the fight against climate change?"

Brooke gave an answer similar to her colleagues' answers and then proceeded to expand on it: "The connection between some of the lifestyle changes our Green Heart program encouraged and long lives was easy to see and thus easier to encourage. The effects of other lifestyle changes were more difficult to see because it would take a lot of people to make any difference, and that difference would be slow to take effect and probably not very noticeable. Those lifestyle changes were hard to encourage, not only because they were difficult to see personally but also because we couldn't afford to lower premiums all that much in reward for the changes. However, there were two reasons we were able to make a difference.

"One was that global warming was already increasing mortality—and would continue to increase it. Even in the United States, droughts, wildfires, extreme weather patterns like hurricanes and storms, flooding on the coasts, and very high or very low temperatures are going to cause a lot of deaths. My insurance company covers people across the country, and the mortality of our policyholders is bound to be affected.

"Two was that climate change was a global crisis, and it was going to affect the health and well-being of everyone. My company is a charitable organization that encourages workers, members and the community to donate time and money to people in need. The people most affected by the effects of global warming were going to be impoverished people in third-world countries that don't have the infrastructure to stand against extreme weather or the resources to adapt to a changing climate. A lot of the initiatives that came out of the Green Heart program were based on helping those who couldn't help themselves. A lot of people are going to step up to the plate if they believe they are helping themselves, their future generations, and those in need."

I was nodding, taking only a split-second to smile at my team. Brooke had made excellent eye contact, had explained her thoughts in a way that was easy to understand, and had spoken for longer than two minutes. She could be the actuary we needed.

I picked out the next question from my notes. "Can you give me examples of some of these 'initiatives' you mentioned? Which were the hardest, and which were the easiest in terms of encouragement by lower premiums or in principle?"

Brooke didn't even glance down at her own notes; she had come prepared. "There were four types of initiatives: individual health, individual responsibility, consumer-voter power (CVP), and global caretaker.

"Individual health was the easiest to implement. It involved lifestyle changes that were beneficial both to the environment and to physical well-being in the short term, and these changes could be tracked and rewarded. An example would be a whole foods, plant-based, and low-waste diet. A plant-based or vegan diet involves consuming no animal products, which saves the planet from deforestation, inefficient use of land and water, and large quantities of methane gas and nitrous oxide, which trap heat in our atmosphere. The addition of "whole foods" and "low waste" means that people won't turn to processed vegan junk food in plastic wrappers but instead focus on bulk grains, fruits, vegetables and plant-based protein. We also encouraged the purchase of GMOs and discouraged the purchase of organic foods. This specific diet was tracked by both receipts and epigenetic markers, and it was rewarded with lower premiums. People found that this diet was much cheaper than they expected, lowered their health care bills, and lowered their life insurance premiums, so the savings were enormous. Other examples of individual health initiatives included proper sleeping habits; reducing technology use; lowering thermostats in the winter for a cooler sleep; short, warm—not hot—showers; adequate exercise; walking or biking to the store or work; and mental well-being (yoga, meditation and outdoor activities) rather than video games and social media. These could be tracked by receipts, epigenetics, house water and electricity usage, Fitbits, etc.

Brooke had made excellent eye contact, had explained her thoughts in a way that was easy to understand. ... She could be the actuary we needed.

"The individual responsibility initiative was more difficult, because we had to come up with creative ways to track both individual behavior and price based on slow, barely discernible changes. One example would be composting. Food that is placed in the garbage to go to a landfill is not going to get the oxygen it needs to break down, so it basically just becomes another piece of trash. But how could we track how much people composted? Well, we decided to team up with local garbage and compost companies. People put out three bins on their driveways: one for trash, one for recycling, and one for compost. The trucks weigh the contents of the bins each week when they take them away, and we charge premiums based on the ratios of compost to trash. We don't directly encourage recycling because we'd rather people use no packaging at all, but it's better to recycle than it is to put it in the trash and lower the ratio. Anyway, this kind of initiative was difficult to value, but my company is great at focusing on the long term, and there are real savings down the road. Other examples of individual responsibility initiatives included solar panels, clean cooking, electric cars or mass transit, insulation, LED lighting, bamboo, water saving, etc. These are all things that don't affect health directly yet should be encouraged."

Brooke took a drink from her stainless-steel water bottle. "The consumer-voter power, or CVP, initiative was an education program based on the power individuals have as consumers and as voters. It involved extensive research into environmentally friendly, ethical brands as well as endorsement of candidates in political races that would fight to implement policies that individuals can't control, such as a carbon tax, construction of wind turbines and nuclear power plants, elimination of harmful chemicals such as those used in refrigeration, etc. Essentially, the CVP initiative became an organization involved in informing via website, campaigns and advertising, and all of this information was backed by extensive, peer-reviewed research easily found by links and references.

"And finally, the global caretaker initiative was focused on the No. 1 solution to climate change: empowering women. It sounds a little weird, but the idea is that the more people we have on this earth, the more carbon emissions we produce. If girls, especially in third-world countries, receive school and family planning education, they will have fewer kids, and the growth in the world population would slow to a more manageable rate. Also, more education usually leads to better health. Thus, the global caretaker initiative was about donating money and time to education and family planning throughout the world.

"As you can see, part of the program was directed toward lifestyle changes that would be rewarded with lower premiums, and part of the program involved political or charitable actions that would be rewarded with the joy of helping someone in need and preserving our planet."

I appreciated the thorough answer and gave Brooke a moment to collect herself before I asked the next question: "You mentioned epigenetics. This was kind of a new field at the time the Green Heart program launched. Can you explain a bit more about it?"

"Genetics is about DNA being passed down from parents, and these genes cannot change throughout a lifetime. Epigenetics is studying how lifestyle and environment can actually switch genes on and off or affect how cells read genes. So diet, sleep, exercise … stress … and also environmental factors like pollution can provoke change in gene activity and expression. This happens through a mechanism called methylation. Insurance companies use various DNA collection methods to determine a person's 'epigenetic age,' or an estimation of one's biological age based on DNA methylation patterns, and they can price their products based on that age. Epigenetics was an exciting innovation for insurance companies."

"What were the biggest issues the Green Heart program faced?"

"Number one was getting the data. Actuaries use historical data to predict the future, but there wasn't a whole lot of data out there about some of the changes we were trying to implement. It took a lot of collaboration with underwriters, data scientists and medical professionals to find the best data at the time and start new studies. Unfortunately, though, new studies were both long in process and small in statistical significance. Something like diet is extremely hard to do a good study on, because there are so many other factors, and the change in mortality is so small at younger ages. Actuaries had the final say on assumptions, and they had to be diligent in tracking progress and changing those assumptions if need be.

"The second biggest issue was fairness. How do we make it so that everyone has access to green behavior? Gas was cheap; electric cars were not. Fast-food burgers were cheap; fresh vegetables not so much. Air quality was worse in low-income areas. The Green Heart program was all about not faulting people for things they couldn't control but rather rewarding positive changes. In the case of equal access to healthy, green behavior, it was necessary for the government to step in. The CVP initiative promoted taxes on things like carbon and unhealthy foods while subsidizing the electric car/pod industry and healthy foods."

"How about the so-called 'skeptics'? Not everyone believed in climate change or pushed back against some of the solutions to climate change."

Brooke nodded. "Monetary benefits helped for climate change skeptics, and helping girls get education is not difficult to convince people is beneficial in every way. For some of the solutions, especially nuclear power and GMOs, it took extensive research and study summaries to convince people that these solutions are not problematic and are, in fact, necessary. Some people still weren't convinced, and that's something we had to live with and find common ground somewhere else."

"Was Green Heart able to find common ground with other insurance companies?"

"The larger the number of people who participate in these green behaviors, the better the effects on mortality would be. It took a large coalition of life insurance companies to start making a difference; we just got the ball rolling. Additionally, this push for a green lifestyle expanded well beyond life insurance to car insurance, health insurance …"

"To beyond insurance."

"Right. To investors, which is really where the change started happening. Companies approved by our CVP initiative began to receive more funding and spread across the country, offering access to environmentally friendly goods and services. The biggest limitations to a movement are convenience and tradition. Those barriers were eliminated when everyone had access and green became normal."

"Expected, even."

"And soon to be required, due to CVP-backed politicians putting green into law."

I flipped a page of my notes. “How has the actuarial career changed?”

Brooke smiled. “From what I understand, the fundamentals have not changed: Actuaries are a group of smart people armed with facts and statistics, making assumptions only when necessary and always geared toward conservatism rather than risk. The difference now is increased reliance on actuarial judgment (we had to make a lot of decisions very quickly and never with as much data as we would like)—also recognition and the expansion of topics. Instead of people trusting actuaries only to price their insurance products, now they are trusting actuaries to count unbiased studies, to point out flaws in data collection, to plot the rise in earth’s temperature and extreme weather patterns, to independently analyze a budget. We have to be thorough, detail-oriented, adaptable, well-rounded, passionate, skeptical and open-minded as well as able to explain our complicated findings in simple terms. Our reputation is high caliber, because we take only high-caliber people.”

“Is it hard to attract high-caliber people to the Minnesotan tundra?”

“Once someone figures out self-driving pods in the snow, no problem!”

We asked more questions, using up as much time as Brooke could allow in her schedule, until we had more than enough material to get a good start on the project. We promised her that we would probably be back to film more once we figured out more of the documentary’s details but that we were planning on structuring the film around her interview answers. We got lunch, our brains brimming with ideas, and even James was convinced we could work with the actuary footage. We then spent the afternoon filming establishing shots of Minneapolis: the Stone Arch Bridge, walking streets, the subway, solar panels, the Sculpture Garden, wind turbines, the city’s nuclear power plant, the surrounding farms, etc.

On the overnight high-speed train ride back to New York, we cut together a few decent clips to show to the boss for approval. With coffee running through our veins, we burst into Megan’s office in excitement and showed her our initial work. The first was a set of contrasting videos showing footage from around the early 2000s tied together with footage we had shot just the day before. From a greasy McDonald’s hamburger to a standard plant-based grain bowl, from a car running on gas to a pod running on electricity, from a coal plant to a nuclear power plant, and many more in rapid succession. The next piece was a set of graphs and pictures with Brooke’s voice narrating how one small part of the program worked. The final piece was Brooke in the conference room with a few inspirational images scattered throughout.

My voice was first. “We are now years down the road, and it’s just been announced that climate change has been reversed. How important was your company’s Green Heart program in that miraculous reversal?”

Brooke was magnetic in look and delivery. “Humans were the ones who caused climate change, and humans were the ones who had to change to reverse it. This had to happen on an individual level, a company level and a national level. The Green Heart program tackled each of those things in a cost-effective, evidence-backed and trustworthy way. We got the ball rolling, but more importantly, everyone did their part.”

The clip ended, and I looked to my boss for approval. A smile lit Megan’s face.

“Wonderful, wonderful. How many actuaries did you interview?” she asked.

“We tested three before settling on Brooke, who you saw in the clip,” I answered. “She impressed us from the start.”

Megan leaned forward in her chair. “Tested? Settled? Are you saying you’re building an entire documentary around this Brooke woman?”

“Well, um … she’s the foundation. We’re going to supplement her with some experts in the topics she brings up.”

Megan shook her head. “I said to *start* with an actuary. Just like climate change wasn’t reversed by one person, this Green Heart program wasn’t engineered by one person. I want more actuaries.” I opened my mouth to protest, but Megan continued, “I also want different areas of the company. The actuaries may have figured a lot of this stuff out, but there’s a lot of people supporting them along the way.” She seemed to be moving toward a better idea for the documentary. “Climate change was a group effort. It’s everyone’s responsibility.” She glanced at Brooke’s face on the paused screen. “Brooke can be your star, but I want this documentary to show that the fight for a cleaner, greener society doesn’t go anywhere without a lot of good people joining in.”

James, Lisa and I nodded, and we got to work. Just like the environmental efforts, our documentary went from the initial idea and grew outward. We had the start: life insurance. For the next step, we went back to the annuity actuary.

“You’ve got two minutes,” Mr. Phillips and I said in unison, and we both laughed.

"In its simplest form," he began, "an annuity is purchased by someone with a lump sum and then pays that person an amount back every month or year for a certain number of years or until they die. So a person might purchase an annuity for a million dollars and receive $5,000 every month. It could be an investment; it could be guaranteed income … *Or* it could be insurance against living too long, also called a payout annuity. With a longer life expectancy, yes, an insurance company is going to have to lower benefits a little bit to offset the number of payments they will have to make to the policyholder. However, people will want to reduce the risk of living longer than they can afford, so they will purchase more payout annuities. People live longer, and insurance companies get more business. Win-win!"

My team expanded our interview pool to include people from areas across the company that assisted in the Green Heart program. The marketing area rebranded the company, the investments area assisted with and followed CVP investment approval, and the HR department trained employees on company changes and green habits. We spoke to underwriters; the medical director; and a variety of architects, solutions engineers and developers in IT.

An underwriter: "Underwriters research and assess the risk of a potential policyholder. We look—in any way we can—at age, health, lifestyle, occupation, family medical history, hobbies, etc. If someone is too risky or unhealthy, we don't give them coverage. If someone is less risky or healthier than average, we give them discounted premiums. My area was essential for giving the Green Heart program's 'discounts.' We had to alter underwriting requirements to include diets, energy usage, transportation and a lot more. Epigenetics was a hugely important change to the underwriting profession."

The medical director: "The medical director role was pivotal in locating as much relevant information as possible—like keeping up to date with the latest in medical journals—and guiding the company in research, in training and in developing underwriting guidelines."

An application engineer: "The IT area was essential for creating new software architecture and improving existing software to handle the new data coming in and the frequent tweaks in product features as all the kinks were worked out."

Then we talked to a few people at the first insurance companies to follow Green Heart's lead. The more insurance companies involved, the more studies could be done and the greater the impact. After that, we spoke with individual investors, local businesses and, finally, Minneapolis residents. The younger people of the next generation were already on to the next fight, so we kept only a clip of a 5-year-old girl shouting, "I am a global citizen!"

The documentary came together nicely, and Megan joyfully submitted it to the contest.

After much deliberation, the results were in, and the top three [films] were announced via the homepage of the contest website.

As we waited for results, I nervously went to the contest website to watch some of the trailers the entrants had to make. Ours was near the bottom alphabetically: *We All Have a Green Heart*. I recognized a few of the filmmakers' names as industry peers and clicked on any trailer that intrigued me. One traveled across the world to get stunning footage of pieces of nature saved by climate-change reversal. One was about the progression of ManBearPig in a series of interviews with the creators of *South Park*.

Then I clicked on the one I was convinced would win. Great footage, powerful message and, most importantly …

"Narrated by Matt Damon? Dang it!" James exclaimed when I showed him the video. "We don't stand a chance!"

After much deliberation, the results were in, and the top three were announced via the homepage of the contest website. James, Lisa and I hovered behind Megan's chair, our eyes flying left to right across her computer screen.

The judges have chosen the top-three documentary films that show the reversal of climate change in a way that will inspire generations to come.

The third-place film shows the world as it is, as it was, and as it could have been. There are haunting images of the harm humankind had caused, brilliantly animated scenes of the path humans were headed down, and beautiful shots of what we see today that we have saved from almost certain destruction. The filmmakers have allowed the images to do the talking, and the message is clear and powerful. People will see what has been saved, and they will want to continue to save it. Although its silence is not marketable to a wider audience, this film is an important exploration into what has been accomplished.

Third Place: Is, Was, and Could Have Been

The second-place film is as entertaining as it is informative. History comes alive through interviews and dramatizations. With a *well-known narrator, slick editing, and modern pop hits, this film will appeal to the masses. The message is glaring. We have come back from destruction, but we must hold each other accountable to never slip into our old ways.*

Second Place: Our Responsibility

"That was the Matt Damon one!" James exclaimed.

Megan's mouse hovered, ready to scroll down to the No. 1 choice.

"It has to be *ManBearPig*," Lisa murmured.

"*We Got Serious?*" Megan inquired.

"No, it's *We Got Cereal*," James corrected.

"Just scroll!" I snapped.

The winning film goes beyond the history book to capture the heart behind the reversal of climate change, a reversal considered to be the greatest unifying achievement humankind has ever seen. This documentary not only highlights the incredible actions of the unsung heroes, a determined group of actuaries that started a movement based on logic and statistics, but also shows the spread of responsibility over time. Climate change did not reverse overnight, and it did not need just a single advocate. This film shows that the best leaders defer to those that know better, the best citizens are both skeptical and open-minded, and everyone must work together to heal the wounds we cause.

First Place: We All Have a Green Heart

We all looked at each other, barely restraining giddy squeals. Brooke called to congratulate us, and we thanked her in return for grounding our ambitious film. Later that night, we all raised a toast.

"To saving the planet, and to actuaries!" ■

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Come Visit Philadelphia This September

By Dave Snell

Throughout this issue, you have seen articles emphasizing the need for actuaries to grow additional skill sets in order to compete with other professionals entering and succeeding in areas formerly dominated by actuaries. Some of them come armed with various AI machine learning techniques and tools that are more cost- or time-effective than our traditional actuarial tools.

The amount of self-education needed now to keep (or get) your edge is daunting. What if you could jump-start that learning curve with two days of training specifically aimed at actuaries—and have each unit of training taught by somebody who is expert in, and actively using, the particular technique in a financial risk environment?

Once again, the Predictive Analytics and Futurism (PAF) Section has prepared such a great learning and networking opportunity for you. This September, the Society of Actuaries 2019 Predictive Analytics Symposium will be in downtown Philadelphia. The symposium will start promptly at 7 a.m. September 19, continue through 5:35 p.m., and restart the following morning with more sessions until 12:15 p.m. If you decide to participate in the PAF Hack-a-Thon, it continues even longer!

HACK-A-THON

For those looking for some truly hands-on experience, or those looking to demonstrate their machine learning expertise through a friendly competition, we have added a half-day Hack-a-Thon to this year's agenda. Attendees who choose to participate in the Hack-a-Thon will compete on teams to build the most accurate model of a real data set. The Hack-a-Thon is open to attendees of all skill levels, and we will ensure that less experienced entrants are teamed up with experts, making this a great learning opportunity. This event will be fast and furious, with four hours to develop a model and submit predictions, so that participants are still able to depart in time to catch a late afternoon flight on Friday.

Whether you choose to participate in the Hack-a-Thon or to focus on your continuing education in predictive analytics, the symposium is a great educational investment.

Here are some of the many sessions you can choose to attend and participate in—and where you can make connections with others who have similar interests:

- Behavioral simulation in actuarial models
- The evolution of predictive models in life insurance underwriting
- Predictive analytics in financial risk management
- Blockchain: Why it's important, and why now
- Jupyter Notebooks: Interactive, sharable documents consolidating input, output and documentation across multiple programming languages
- Industry best practices for data protection
- Sharing Shiny applications
- Insurance innovation and the AI revolution
- Dangers of overfitting: Myths and facts of predictive analytics
- From concept to commercialization: An agile approach to analytics use cases
- Convolutional neural networks and generative adversarial networks: Moving beyond basic neural networks for innovative advantages
- Visualization: A picture speaks a thousand words
- Multivariate feature engineering: Beyond simple data preparation
- Get your voice heard (how to get funding for predictive analytics projects)
- Using predictive models for life insurance assumptions
- How insurance startups become competitive
- Data science in the cloud in under an hour
- Nonquantitative considerations in insurance: Behavioral economics—the reason your strictly analytic models will fail!
- Bayesian model applications in insurance
- Natural language processing in the insurance industry
- How can an actuary become a data scientist?
- Why your company needs a data strategy
- Assessing credibility of predictive models
- Epigenetics—the superset of all things genomic: How will it change our lives? Also, how after-issue genetic testing can provide big savings
- Making the most of your R projects: Auditable, interactive R sessions with RStudio
- General insurance applications of predictive analytics
- Developing web application with R Shiny
- Introduction to computer vision and its applications in insurance
- Languages of predictive analytics: A Tower of Babel?
- Building an actuarial data science team
- Practical aspects of predictive models
- Using natural language processing to monitor and detect emerging risks

All of these are opportunities to learn from experts who empathize with your needs, speak in terms familiar to actuaries, love their topics, and want to share their knowledge and experience with you. Unlike a book or an online course environment, you can interact and forge lasting connections.

This is our third annual predictive analytics symposium, and it has been refined and updated to give you the best guide we can through the learning curve in a short time period. Past attendees have loved it. We hope that you will as well.

Please register at *https://www.soa.org/prof-dev/events/2019-predictive-analytics-symposium/*.

My co-chair, Xiaojie (Jane) Wang, and I look forward to seeing you! ■

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