SOCIETY OF ACTUARIES Forecasting and Futurism Section

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Forecasting & Futurism

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Forecasting & Futurism

NEWSLETTER

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This newsletter is free to section members. Current issues are available on the SOA website *(www.soa.org).*

To join the section, SOA members and non-members can locate a membership form on the Forecasting and Futurism Section Web page at *www.soa.org/forecasting-futurism.*

FROM THE EDITOR:

"What's in a Name?"

By Dave Snell

My favorite play by Shakespeare is "Romeo and Juliet." In Act II, Scene 2, Juliet utters that famous line: "*What's in a name? That which we call a rose By any other name would smell as sweet."* Shakespeare had the ability to turn words into imagery—and beyond that into a full sensory experience. I could see and smell the rose just as if it were before me. Juliet's point was that her love, Romeo, had an unfortunate surname and it was unfair for her family to prejudge him on that basis.

The reality though is that we all tend to attach credence (or sometimes disbelief) in names. In most cases this is a natural outgrowth of our experiences.

This issue continues a theme we started in January about the limits of our classical actuarial tools. A lot of new "names" are gaining popularity (complexity sciences, predictive modeling, advanced business analytics, agent-based models, autoregressive-moving-average models, etc.) and sometimes it is tempting to assume that just because something has a scientific sounding name, it must be superior to older, less expansively named tools and techniques.

In a world where the tools of the past seem to have broken down in the accurate forecasting of market trends, natural disasters and risk in general, some may feel it is time to throw out the incumbents and start anew with these fancy, promising technologies with multisyllabic names.

In this issue, we continue to introduce some new ideas; but we also have tried to temper the enthusiasm with some tried and true reality checks.

Kurt Wrobel wrote an excellent article for the January 2012 issue of *Health Watch*, the newsletter of the SOA Health Section. In "The Actuarial Profession and Complex Models: Knowing the Limits of Our Knowledge," which I am reprinting here with permission, Kurt chronicles the dangers of some common mistakes that people make now with the multitude of data available to us: presentation of data with little or no credibility, mistaking correlation with causation, biased data mining, and narrative bias. Quoting from his article, "To the extent historical data no longer accurately reflects a given phenomenon" … "even the most sophisticated data analysis will not adequately predict the future."

In harmony with Kurt's contribution, I have reviewed an irreverently engaging book by Ben Goldacre, M.D., titled *Bad Science*. Dr. Goldacre did not intend this strictly for actuaries. He is trying to educate the public about the many ways they have been duped by the Big Pharma (pharmaceutical) companies and others who have learned how to misapply statistics for their own purposes. I learned a lot about good science practices in the course of reading his many detailed exposures of *Bad Science* practices. As actuaries, we need to be aware of how to conduct and present our own studies in a manner that is accurate and ethical and less susceptible to accidental (or not) misinterpretation.

Another book review was submitted by Ben Wolzenski. He reviewed *Growing Artificial Societies – Social Science from the Bottom Up*, by Joshua Epstein and Robert Axtell.

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"WHAT'S IN A NAME?" | FROM PAGE 3

This is an exciting extension of our Forecasting & Futurism (F&F) focus on agent-based modeling, and Ben describes how the authors built Sugarscape, where the agents migrate and change the characteristics of their society by following simple rules of self-interest. I was privileged to meet Robert Axtell and see his presentation of Sugarscape; and I am really excited that Ben is now building his own version and will be showing an insurance application at a session this year at the 2012 Life & Annuity Meeting and the SOA 2012 Annual Meeting.

Donald Krouse, our chair for 2012, also gives us a wake-up call to our limits in his article, "Challenging Old Paradigms – What Are You Going to Do?" Donald, along with Clark Ramsey, our vice chair, attended this meeting in March 2012 and passed along a disturbing quote about equity returns: "What other key assumption has been off by more than 15,000 bps within a decade?" Donald and the other summit attendees came away with the conclusion that "approaches used historically, and still very much in use, may end up being woefully inadequate."

Donald also gives us another chairperson's column (his second this year) and it is upbeat despite the summit concerns. He summarizes the ways in which the F&F section is very actively putting together sessions, collaborating with other sections, and funding research initiatives. He also adds a couple important enhancements to the SOA *Risk is Opportunity* byline.

Dave Snell

Following our artificial societies, we have an excellent summary titled, "Artificial Intelligence: What Is It and How Can I Use It?" by Brian Grossmiller of an Artificial Intelligence (AI) course he took through Stanford. This course broke all previous attendance records when it attracted over 160,000 participants from all over the world. Brian, in his article, highlights some of the special characteristics of Genetic Algorithms (GA) – a topic where he has become an enthusiastic advocate and mentor. Brian reveals some of the science and the art of developing genetic algorithms. Please read his useful summary; and then I hope you will come to our GA workshops, where he and I will be teaching a workshop on genetic algorithms at the 2012 Health Meeting and again at the SOA 2012 Annual Meeting.

Rounding out our issue is an educational yet highly readable article from Richard Xu, a Ph.D., who clearly describes technical items such as how to use the R statistical programming language, for autoregressive-moving-average (ARMA) models. Richard's article, "How to Win an iPad2," was a result of our contest to predict the monthly unemployment rate from March 2012 to September 2012 Instead of just keeping his knowledge to himself, he generously provides a refresher on regression and time series models.

Yes, Romeo was stuck with an unfortunate name (Montague) when he tried to court Juliet Capulet. The Montagues and Capulets were predisposed to dislike each other. Forecasting & Futurism, however, has made a name for itself as an innovative section that collaborates with Actuary of the Future, Investment, Health, Management & Personal Development, Technology and other sections as we all help each other to help the profession. Perhaps through our efforts, "that which we call an actuary," might someday evoke an image of the "consummate risk management professional." ▼

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FROM THE CHAIRPERSON:

Future = *Unknown* = *Risk* = *Opportunity*

By Donald Krouse

Welcome to another exciting issue of the Society of Actuaries' Forecasting and Futurism Section Newsletter. This issue again brings a wide range of articles. Ideally you will find many of interest.

Your section council has been busy these past few months. We continue to work opportunities for participation in research initiatives and Delphi studies. We have once more agreed to provide funding for the Actuarial Research Conference (being held in Winnipeg, MB, this year), and our latest iPAD contest, predicting unemployment rates, is well underway. At this time, we have a total of 10 meeting sessions identified for 2012 (two at the Life & Annuity Symposium, three at the Health Meeting, four at the SOA 2012 Annual Meeting, and for the first time, one at the Valuation Actuary Symposium). We are also co-sponsoring additional sessions. If you plan on going to an SOA meeting this year, please consider attending one of these.

The Forecasting and Futurism Section also co-sponsored the first "Long-Term Financial Planning Summit: Challenging Old Paradigms," which was held March 25 in New York. Clark Ramsey and I represented the section at this event and have submitted an article in this newsletter describing our experiences. Suffice it to say that I found this to be an excellent summit, both professionally and personally. I hope that my article stimulates your "forecasting and futurism" synapses like my attendance at this summit stimulated mine. Clearly the tools and techniques we are developing and encouraging within this section will be of assistance in resolving some of the complex issues raised.

Looking forward, the fall will bring three new members to our council. If you haven't already done so, please consider what contribution YOU may be able to make to the section either on council, as a friend of the council, or as a volunteer in any of our many initiatives. Please don't hesitate to contact me or any council member to discuss the possibilities.

Future = Unknown = Risk = Opportunity

Regards,
Donald

Donald Krouse

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Artificial Intelligence: What Is It and How Can I Use It?

By Brian Grossmiller

Recently I had the opportunity to participate in an online class which provided a very thorough introduction to the field of artificial intelligence (see *https://www.ai-class.com/* for the course materials). There are several exciting potential applications to an actuary's practice. In this article I will share some of the key definitions along with some possible applications.

A key definition in the field of artificial intelligence is an intelligent agent. This is what we are trying to build, an agent or system that (ideally) behaves optimally in its environment. Intelligent agents can vary considerably in their complexity, from simple agents that respond with a reflex reaction to agents that actually learn from their environment and can adjust their actions for unexpected impediments. The components involved in an intelligent agent will of course depend on the application; these can include software, robotics, cameras, keystroke inputs and computer files.

An intelligent agent consists of three parts: a sensor, a control policy and an actuator. Sensors can be cameras, optical character readers, or an input section of a computer program and are the means by which the agent perceives its environment. The control policy is the element that decides what action to take based on the agent's perception. As a simple example, a search engine would perceive a keyword entered into it and the agent would decide what list of URLs to display based on a set of rules. Actuators are the means by which an agent responds to its environment; these can be anything from robotic arms to simple text outputs on a monitor.

One of the more basic intelligent agents is a problem-solving agent, which attempts to reach a goal while maximizing its performance according to a metric. This type of agent can be constructed through searching, where it is typically designed to find the optimal path from a starting point to its defined goal state. A familiar example is GPS navigation, which finds the shortest path from your current location to your destination. In this case the agent finds a path designed to minimize distance or travel time.

An interesting type of search strategy includes a heuristic function, which provides an estimate of the cost to reach the goal state from any point along the way. This function is combined with the known cost to reach each point in an effort to find the cheapest solution in the shortest amount of time. A key criterion for a heuristic to work in this fashion is that it has to be "optimistic," that is, it never overestimates the actual cost.

Generating heuristics can prove to be an interesting problem in and of itself. Some strategies include solving a "relaxed" problem, where some restrictions of the actual problem are ignored, or looking at a subset of the problem. There are also techniques for learning heuristics from examples of solutions.

A very powerful and exciting application of artificial intelligence is constructing agents that learn from examples. This approach can build programs to solve problems that are excessively difficult or tedious for a programmer to design directly. The main categories of machine learning are reinforcement, unsupervised and supervised learning.

Reinforcement learning depends on some metric which determines whether an outcome is favorable or not. In a game such as chess, this would be provided in the form of a win or a loss. Over a large number of games the agent can determine which of its actions tend to lead to a favorable outcome. This approach produces agents designed to take actions to optimize their expected result.

In unsupervised learning the data provided are not labeled. The agent attempts to learn the structure and features of the data. Notably, agents are not given feedback as in the other methods; the result is usually a summary of the data.

Supervised learning involves collecting pairs of inputs and outputs. The outputs can be generated from humans, or perhaps be a set of related measurements. The dataset is used to train the agent to infer the output for inputs not in the training set. Actual applications may blur the distinction between these categories. For instance, semi-supervised

learning problems typically have a labeled subset of data and a much larger unlabeled dataset. Results can have greater accuracy than a fully unsupervised agent without the potentially considerable expense of labeling a large dataset.

One method that has shown promise in actuarial applications is Genetic Algorithms (GAs), which are search heuristics modeled on natural evolution. GAs utilize a fitness function and develop optimal solutions over a series of generations by combining and mutating the top performers. Typical problems involve a large number of possible solutions with a readily calculable fitness function where computing each solution directly would be prohibitively time consuming.

A first generation is developed randomly and scores under the fitness function are computed. The top performers are randomly combined together to develop a new generation, usually with a random mutation of a small number of genes. The new generation is scored under the fitness function and the process is repeated recursively. When the initial population contains a diverse set of solutions, the child solutions tend to be radically different from the parents', which often leads to significant improvements in performance in the first few generations. The solutions become increasing similar, since they are drawn from the same gene pool, so later generations typically show more marginal improvements in performance.

When the generations become too similar, the GA version of inbreeding occurs, which limits further gains. Part of the "art" in developing GAs involves striking good balances between retention of the top performers and introduction of mutations. Keeping the best of a generation and affording them "breeding rights" helps to prevent their children from regressing. However, mutations can sometimes bring about innovative advances.

This technique is being applied to selecting an optimal provider network for a health plan. The fitness function in this instance scores each provider according to their relative cost efficiency and produces solutions that maintain an adequate panel of providers in each area of medical practice. In this situation, there are a large number of providers and many possible solutions entailing different combinations of groups of providers. This provides an excellent starting point for developing a narrow panel, as selecting a panel by hand can be very tedious and may overlook better performing alternatives.

In addition, a GA approach has been successfully implemented in Life Insurance Asset/Liability Management. In this application, the fitness function measures volatility driven by shocks to the interest rate curve; the GA minimizes this volatility by generating optimized asset allocation strategies. This has produced strategies which provided superior minimization of interest rate risk over traditional methods (see Ben Wadsley's article, "Are Genetic Algorithms Even Applicable to Actuaries?" in the July 2011 issue of the *Forecasting & Futurism Newsletter*, page 6).

There are many interesting applications of artificial intelligence being deployed today; I invite you to review the course materials online. In addition, a free series of excellent computer science courses can be found on Udacity's website at *http://www.udacity.com/*. ▼

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Introduction to Artificial Intelligence, taught by Professor Sebastian Thrun and Professor Peter Norvig. https://www.ai-class.com/

Brian Grossmiller

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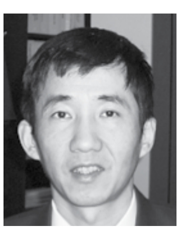
How to Win an iPad2

By Richard Xu

In the January 2012 issue of *Forecasting & Futurism Newsletter*, there was an announcement about the 2nd annual iPad2 forecasting competition. The competition is to develop a model to predict the monthly unemployment rate (UNRATE) from March 2012 to September 2012. The winner's model should have the smallest sum of squared deviations between model predicted values and the actual data over the forecast period of six months. Data is limited to the Federal Reserve Economic Data (FRED) database, which has about 35,000 historical economic data and is available free of charge, with the exclusion of variables that have direct unemployment information.



Richard Xu

Many actuaries are tempted to get into the race and win a nice iPad2, but find themselves with a lack of available model to start with. But in fact, almost all actuaries have the educational background to build a regression or time series model from either their college courses or required actuarial exams. The problem that many actuaries are facing is that they infrequently, if ever, use these in their actuarial works.

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Without much work experience, many actuaries may forget linear regression models or time series analysis, and so winning an iPad may look like a daunting task.

The purpose of this article is to provide a refresher on regression and time series models so that actuaries will feel more comfortable and confident to build a forecasting model based on these fundamental tools and apply them in their actuarial works if such models are appropriate.

Simply put, a linear regression model can be described by an equation

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_n x_{in} + \varepsilon = \Sigma_j \beta_j x_{ij} + \varepsilon_i$$

where y_i is called *response variable*, or *dependent variable.* This is the variable that has been observed in experience and is to be predicted by model. x_{ij} are called the *explanatory variables*, *covariates*, *input variables*, or *independent variables.* β_j are coefficients to be estimated in model building process, and ε_i is error term.

To make a valid linear regression in this basic form, several assumptions are needed. A linear relationship between response and explanatory variables is obviously one. In most applications in finance, this usually is not a problem. Either the relationship is inherently linear, or it can be well-approximated by a linear equation over short ranges. In addition, the error term ε_i must follow normal distribution with mean value at zero and a constant variance, i.e., $\varepsilon_i \sim N(0, \sigma^2)$. Other requirements include that y_i is representative of population, observations are independent from each other, and x_{ij} is error-free.

The most common method of estimating β_j is least squares, in which β_j is chosen such that $RSS = \sum_i (\hat{y}_i - y_i)^2 = \sum_i (\Sigma_j \beta_j x_{ij} - y_i)^2$ is at its minimum, where RSS stands for Residual Sum Square, and $\hat{y}_i$ is the fitted value. There are close form solutions for β_j in matrix form. The other estimation is maximum likelihood to find β_j so that product of probability at all data points is at its maximum. Under the normal distribution, it can be proven that both estimations will give the same result.

Unless it is a very small data set, it is not possible to build a real model just with pen and paper. You have to rely on computing software to find β_j. The choice of statistical software is quite abundant, such as R, SAS, SPSS, MatLab, MiniTab, etc. Actually, for a very small simple application, you can use Excel built-in function by selection "Data" -> "Data Analysis," but it has the limit of only 16 explanatory variables. For a large or complicated model, computing software is the only viable choice. Among the actuarial community, the two most commonly used are R and SAS. The R is free software under GUN license, while the later one is a commercial product. The examples in this article will be illustrated by using R. R is unique, not only because it is free, but also because there is a large online community and a core statistics team to support it. You have a wide choice of education and academic materials about R, and there will never be a shortage of statistic tools in R to build any particular model. As of now, there are 3,738 packages available on top of already abundant basic tools that come with the R system, and the number is still growing.

Let's look at an example on how you can work out a linear regression model. Here is a 10-year revenue data of a public insurance company. We would like to know how the revenue grew in the past 10 years and predict what revenue will be for 2012. With the data, you can save to a text file or CSV file called "iData.txt" with common as separator and header included.

Year	Revenue
2002	2.382
2003	3.175
2004	4.021
2005	4.585
2006	5.194
2007	5.718
2008	5.681
2009	7.067
2010	8.262
2011	8.830

Inside R, you can use the following command to first load data into R system, build a linear regression model, and show summary.

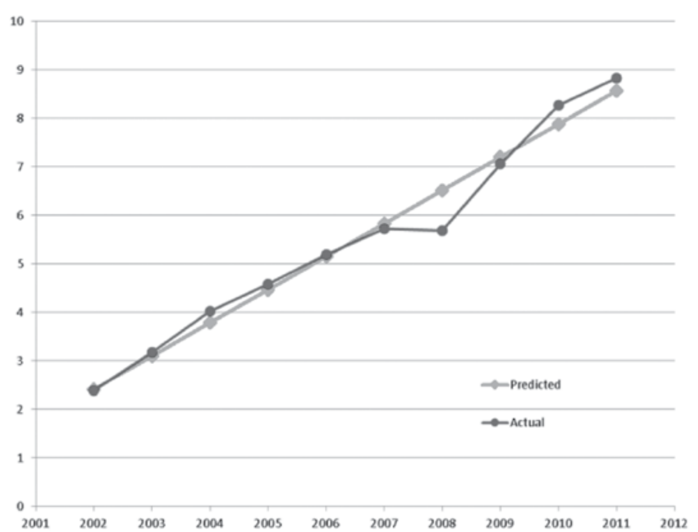
```
>iData<-read.table("iData1.txt", header = TRUE, sep=",")
>iModel<- lm(Revenue~Year, data=iData)
>summary(iModel)
Call:
lm(formula = Revenue ~ Year)

Residuals:
     Min       1Q   Median       3Q      Max
-0.83489 -0.09530  0.05885  0.20709  0.38025

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -1.365e+03  7.893e+01  -17.29 1.27e-07 ***
year         6.829e-01  3.934e-02   17.36 1.24e-07 ***
---
Signif.codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3573 on 8 degrees of freedom
Multiple R-squared: 0.9741,     Adjusted R-squared: 0.9709
F-statistic: 301.4 on 1 and 8 DF,  p-value: 1.235e-07
```

Revenue (2002-2011) - In Billions



In summary, we can see that the slope is 0.68, which is the annual revenue increase rate. For the year 2012, the predicted revenue is 9.25. Actually, you will have more statistical information about the model, such as the confidence level of the coefficient, goodness of fittings, etc.

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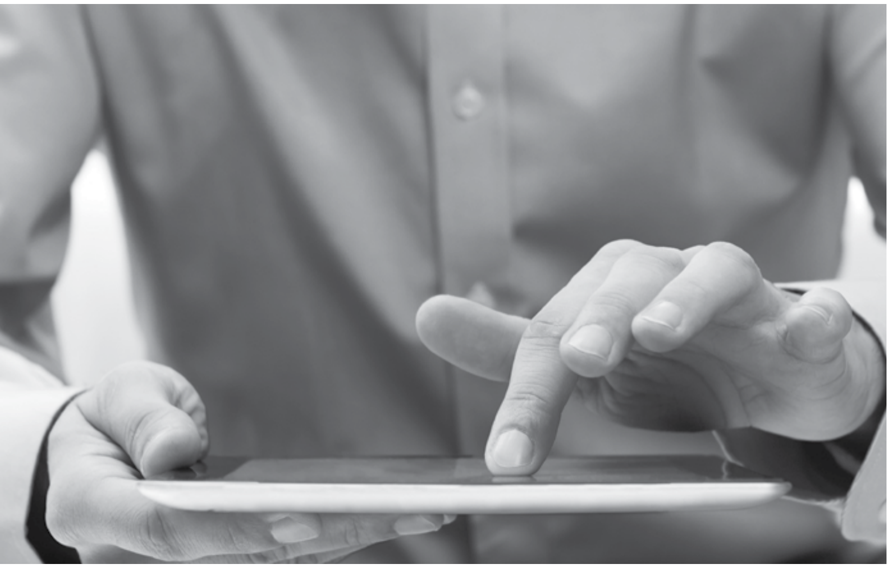

For linear regression models, the most often used criteria to assess the goodness of fitting is R^2, which is defined as a ratio of variance that has been explained by the model to the total variance in the data. However, the R^2 could be misleading as more explanatory variables will always increase R^2 even though the additional variables may totally be irrelevant, such as purenoise. This is called an over-fitting problem in modeling, and can be a serious issue as a model may have a perfect fit to data that are used for modeling, but very poor in application of real life. The adjusted $\bar{R}^2$ is better, as a penalty is added to it such that the increase of R^2 has to be statistically large enough to overcome the penalty of additional variable. A more universal approach is the maximum likelihood, where Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC) can be used to assess the model and to avoid the overfitting issue.

LINEAR REGRESSION AND TIME SERIES ARE VERY BASIC STATISTIC TOOLS. YOU ARE NEVER SHORT OF APPLICATIONS IN ALMOST ALL INDUSTRY FIELDS.

Once you are comfortable enough to build a linear regression model, you can naturally extend your skills to time series, where input data is a sequence of data points at successive time instants usually with uniform time intervals. There are two basic models that are conceptual extensions of linear regression model. One is the autoregressive model (*AR*), in which explanatory variables include the response variable itself, but at an earlier time. For example, the unemployment rate at a certain month is highly correlated to levels of several previous months, and can be explained in large part by its immediately previous monthly rate. A mathematical equation for a simple *AR* model can be stated as

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \cdots + \alpha_n y_{t-p} + \varepsilon_t$$

This is an autoregressive model with p terms, usually denoted as *AR(p)*. The other model is called moving average (*MA*) model, where response variable is a function of previous error terms. An *MA* model with q terms can be represented by

$$y_t = \mu + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \cdots + \theta_n \epsilon_{t-q} + \varepsilon_t$$

When you combine these two models, you have the autoregressive–moving-average (ARMA) models, sometimes called Box–Jenkins models. Usually the notation ARMA (p,q) is used to refer to the model with p autoregressive terms and q moving-average terms.

There are basic functions in *R* that you can use to model the time series, such as "arima." Also, there are several packages you can install within *R* to do some special analysis. Just like linear regression models, you need the right commands to load data, build a model, and assess the model. Usually, the procedure is iterative in nature. You will try different variables and can even include an interaction term, until you find an optimal model that best explains the data.

Linear regression and time series are very basic statistic tools. You are never short of applications in almost all industry fields. Extensions of these two techniques to overcome various limits have led to numerous other modeling tools, such as generalized linear model (GLM), mixed effect model, GARCH, etc. Although the direct application of linear regression and time series in insurance is very limited, the GLM eventually finds its way into actuarial science and now we are witnessing the explosive applications of GLM in insurance, known as predictive modeling.

Data is always a concern in modeling, but actuaries are considered as number experts and never underestimate the importance of data and difficulty of understanding and cleaning data. In reality you have all different kinds of issues to consider, such as sources of data, quality and quantity, missing variable, etc, and actuaries are usually clever in finding their way out. Luckily, in this competition, data is less an issue. The main question is to find the right explanatory variables from the list of 35,000 series.

A few words about *R*. Many actuaries find it very intimidating to start to learn *R* after they are used to graphic user interface (GUI) by clicking on buttons or menu for so many years. It truly is, at the beginning, especially when you have never had the exposure to the command line environment. A good start will be a few simple examples that you already know what the model is all about so that uncertainty about the model itself is removed leaving only questions about *R*. As you progress in both scope and depth of modeling skills, you will find that *R* is a very powerful and versatile tool for data analysis and visualization.

To win an iPad2 would be a very nice achievement, but you will gain more even by just participation. With the coming of the big data era and wide acceptance of predictive modeling in insurance, actuaries are faced with more demands on their modeling skills and their tool choices. This competition is a very good starting point for actuaries to try these, which is perhaps the main reason why you should participate in it. ▼

Challenging Old Paradigms—What Are You Going to Do?

By Donald Krouse

The Long-Term Financial Planning Summit: Challenging Old Paradigms was held on March 25, 2012, the day before the SOA Investment Actuary Symposium. The summit was initiated by the SOA Investment Section in collaboration with the Forecasting and Futurism, Social Insurance & Public Finance, Long Term Care Insurance, and Pension Sections. Though sponsored by the Society of Actuaries, this "think tank" was attended by many non-actuaries including economists, academics and members of PRMIA (Professional Risk Managers' International Association) and the CFA (Chartered Financial Analyst) Institute.

The intent of the summit was to serve as an initial step in addressing issues related to long-term expectations. To put the "issues" in context, the following is extracted from the introduction of the summit materials:

> *For several decades, expected returns have served as the crux of "long-term" financial planning for individuals, pensions, and many social programs. Unfortunately, after a decade of sub-par returns, it is evident there are shortcomings to this approach. Equity returns were essentially flat in the 2000's, yet annual expected returns for the asset class commonly hovered around 10%. What other key assumption has been off by more than 15,000 bps within a decade?*
>
> *Historical returns often serve as the foundation for establishing future return expectations. However, it's debatable whether historical returns are even relevant. We live in a complex global economy. Technological advances can change our perception of reality in an instant and can drive not only how global wealth is allocated among and within countries, but also how the global population is distributed. We are arguably reaching a point where the world is reaching peak natural resources as it relates to population growth, food, water, and energy. Debt historically was used to generate funding of opportunities to produce growth in these natural resources. A portion of the results of expected economic growth were then used to repay the debt, as it were. Can this paradigm work today and into the future? Even more, economic cycles are driven by demographics and technological advances yet, at the same time, are one of the largest drivers of how both factors evolve. Improving our understanding of these relationships, and recognizing the weaknesses of traditional expected return methodologies, should lead to more realistic expectations and to more sustainable social policies.*

Clearly the task of addressing the above is daunting.

During the day the issues were approached from multiple angles. Methodologies used in interpreting historical returns were discussed, both common practice and pitfalls (which are often the same!). Key factors were analyzed, including demographic trends, government/entitlement programs, technology, and geopolitical considerations. Methods to define return expectations absent historical information were reviewed. Finally, there was significant discussion (and debate) around what a "sustainable" system would encompass, including consideration of social programs, tax incentives to savings, mandated savings/benefits, etc.

While many of the topics discussed apply generally, the main focus of the day revolved around pension plans and their funding levels. Numerous observations were shared such as the impact of substitution of DC for DB plans (transferring risk to the plan participants), and substitution of cash balance plans (which in general present a reduction to the "funding" provided by the plan sponsor). Most significantly, funding levels, both as determined using "traditional" approaches, and as "required" under current regulation (which evolved from these traditional practices), were contrasted against what "modern" valuation techniques would indicate. While the actual amount of funding will not be known until the last benefit is paid, virtually any comparison of the "old" versus "new" approaches, at least in our current financial environment, results in much higher

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funding requirements using the new approach. Inertia, combined with lack of appetite to recognize potential shortfalls, perpetuates adherence to the historical methods by both politicians and private plan sponsors.

A fundamental conclusion emphasized during the summit is that approaches used historically, and still very much in use, may end up being woefully inadequate. Should this be the case there would be dire consequences to most government retirement plans and most private DB plans. By extension, DC and cash balance plans could also end up being insufficient to meet most retiree needs, as the premises underlying the "funding" requirements of these are also derived from similar historical methodologies.

Of course not all is doom and gloom. With improved technologies, increasing GDPs, economic growth, etc. even apparently low funding levels may still be sufficient. But enter demographics. In the United States and most of the "developed" world, there is a demographic headwind that culminates in fewer working members of society relative to the total population. All else equal, GDP per person will be expected to decrease. The repercussions are painfully obvious: even if a retiree had "enough" funds, who would provide his or her medical and other services? The answer is a diminished working force that, via supply/demand, would simply drive up the cost that the retiree pays. Thus the retiree might never have enough funds, or at a minimum, would need to defer retirement and/or supplement retirement with part-time work.

THE REPERCUSSIONS ARE PAINFULLY OBVIOUS: EVEN IF A RETIREE HAD "ENOUGH" FUNDS, WHO WOULD PROVIDE HIS OR HER MEDICAL AND OTHER SERVICES?

But what about immigration, you ask? Sure, a developed country such as the United States may be able to import a working force, but this then raises at least three further questions: 1) worldwide, does such a workforce exist? i.e., do the demographics support this possibility AND is this population capable (through education, training, and proximity) of providing this labor? 2) what price would such a workforce (if it exists) demand? and 3) what would be the societal repercussions of large-scale shifts of people from different cultural backgrounds (both good and bad)? These are not easy questions to answer. From a demographic perspective there may be sufficient worldwide labor; but at this time, it is concentrated in "developing" parts of the world. To capitalize on this potential labor force would require significant investment in these nations.

So, as a person with a strong interest in forecasting and futurism, how do I "size up" the possibilities that exist for me? Where will I, a typical U.S. citizen a couple decades from retirement, end up? Should I (selfishly) focus on "me and mine" or subscribe to the adage that "a rising tide raises all ships?" From my perspective, I view the question as, "What specific actions can I take to potentially better my personal situation, without causing detriment to others?"

Perhaps I am already doing enough: I maximize my 401(k) contribution and I try to save some additional amount of my

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CHALLENGING OLD PARADIGMS … | FROM PAGE 13

salary each year. I also support my children's education (so they can, ironically, demand more money from my generation at some future date), and I contribute to and volunteer at charities that promote improving peoples' contributions to society (temporary shelters, (re)training and education, defense of children, etc.). The above is maybe a good start, but attending this summit got me thinking about further possibilities including directing some of my savings/investments/charitable contributions into areas such as 1) infrastructure of developing nations, 2) technological advances focusing on delivery of services (i.e., so fewer people are needed to perform the same amount of work), 3) promotion of the family unit (however one defines "family," the underlying premise being one of mutualism), and 4) general improvement of quality of the environment, and hence living conditions, via clean water, green energy and environmental/resource conservation. I've also recommitted to my savings regimen and am making my home as comfortable as possible. I plan to stay there a long time, ideally provided for, at least in part, by my family.

To what I extent I follow through on these ideas remains to be seen. Everybody's approach will be different, and no one has a crystal ball. Perhaps all this discussion will be moot if a Black Swan (asteroid impact, plague) strikes the earth tomorrow. Absent cataclysm, will world governments still exist in 30 years, and if they do, will the demands of an older generation indenture the workforce? Will the workforce have the ability to meet such demands? Even with ability, will the workforce be willing to meet such demands, or will rebellion ensue?

So what are your thoughts? What are YOU going to do (if anything)?

These are not rhetorical questions. I welcome your ideas. Responses may even be published (anonymously if you wish) in the next newsletter. ▼

The Actuarial Profession and Complex Models: Knowing the Limits of Our Knowledge

By Kurt Wrobel

In very simple terms, actuaries are in the business of predicting future liabilities associated with financial products. In attempting to quantify this future cost, we use historical experience and then make adjustments to account for expected changes in unit cost and utilization to estimate future liabilities. And, in keeping with our professional standards, we follow the best statistical methods available to impartially predict future costs. As I will highlight in this article, I believe that gradual changes in the business environment have made this impartial prediction process much more difficult for our profession, but still possible to achieve. Following the initial discussion, I will outline some steps that we can follow to ensure a more rational and productive approach to data analysis.

The Problem: So What Has Changed?

Over the past several years, we have seen changes in the business environment that have impacted our ability to ensure that our organizations make appropriate decisions based on the available data, including:

- Easy access to data and the growth of software packages that allow more sophisticated data analysis and the appearance of more sophisticated data analysis.
- Increasing expectation for the usefulness of data as popularized by several books and movies.
- The degree of dislocation and change in our economy has made historical data less useful in predicting future results.

Kurt Wrobel

Easy Access to Data and Software Tools

With the remarkable progress in software and access to data, companies have effectively democratized data analysis across large organizations giving access to a significant number of individuals with less intensive statistical training and without the same degree of professionalism applied to impartial data analysis. In many respects, this can be a real positive for a company. The actuarial profession certainly does not have a lock on the appropriate use of data in a business environment and a company could benefit from more people analyzing data. That being said, the increased democratization of data analysis has a serious downside as less sophisticated individuals present data analytics. Although the problem can take on many forms, I have highlighted some of the more challenging problems.

Presentation of data with little or no credibility. This is an issue that is self-evident to most actuaries. Throughout my career, I have consistently seen people draw inferences from data that lacked almost any credibility. Alternatively, in response to a concern about credibility, someone will ask about a specific break point where the data suddenly becomes credible rather than think about the underlying distribution associated with different population sizes. For example, the stylized chart on page 17 highlights the distribution of medical loss ratios at different underlying membership levels using a simulation process.

As highlighted above, the distribution of potential outcomes becomes more tightly centered around the mean as membership increases, but there is not a specific break point where the data suddenly become credible. In addition, a single observed loss ratio with a small membership base provides little information on what the true underlying mean would be if the simulation were run numerous times.

Mistaking correlation with causation. As we have all learned in basic statistics, correlation does not necessarily imply causation. Some interesting examples include:

- A win for the Redskins in their last home game prior to Election Day coincides with the incumbent party being reelected.
- Greater sun spot activity produces an increase in the stock market or GDP.

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- When a team from the old NFL wins the Super Bowl, the stock market will rise.

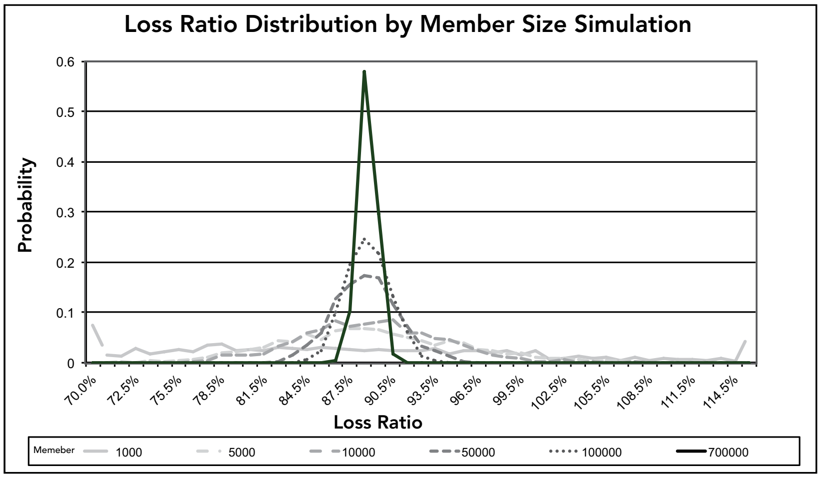
- U.S. stock markets are weakest following the election of a new president

The problem, of course, is that less sophisticated people will present and draw inferences without adequately controlling for other variables that could be driving the underlying causation.

Biased data mining. Without the same degree of professionalism and commitment to impartiality, some data analysts will sift through data to find specific data points that will support their particular position. For example, in a linear regression, an analyst could engage in "regression fishing" where several regressions are run with numerous explanatory variables with only the most favored result—as measured by the strength of the fit—presented. By not accounting for the inherent biases associated with running several regressions to find the best fit, the conclusions drawn from a partial presentation of the facts are biased and inaccurate.

Narrative bias. While biased data mining involves the abuse of statistics to develop a particular conclusion *before* the prediction, the narrative bias problem represents conclusions or "sound bites" drawn *after* an event has occurred. In this case, a data analyst or commentator will draw a conclusion to the perceived event that is consistent with the broader story he wants to tell to the organization. The problem is that the perceived event was likely the result of a complex model that could have just as likely produced this or several outcomes.

In a simple example of this problem, one could think of someone drawing inferences on why a random throw of the two dice produced a particular result—say a three—after the roll has occurred. While actuaries or more sophisticated analysts may attribute this result to an event that could have occurred given the distribution of possible outcomes, less sophisticated analysts may attempt to explain this result with an elaborate explanation. In a business environment, this story will typically support a particular business policy that they had been advocating.



Loss Ratio Distribution by Member Size Simulation

This problem is especially troublesome for actuaries. Using the dice example, while we could have correctly said that the most likely outcome was a seven and that we would expect an entire distribution of outcomes, we could be perceived as incorrect in our prediction and our reputation compromised because the most likely event did not occur. With the perception then created that the actuarial prediction was incorrect, this could then provide an opportunity for someone else to introduce their own simplifying narrative on why a particular event occurred. Using the dice example, someone could say that their lucky rabbit's foot or dice throwing technique produced the three and that the actuary who predicted the seven did not adequately account for their abilities. As a result, in the next prediction cycle, the story now becomes that the actuary should better account for their skill or luck in throwing the dice. Continuing with the story, if the next throw of the dice produces a more likely result—say a seven—then nothing will be heard from data analysts who criticized the prior prediction. Of course, if another three is produced, the criticism will be immediate and our prediction abilities questioned once again.

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Increasing Expectations for the Usefulness of Data

We live in a business world that has come to increasingly worship data analysis and its potential to answer important business questions. In many respects, this represents an effective strategy. We have seen many companies (Capital One) and even sports team (the Oakland As) effectively deploy strategies to dramatically improve results. (Admittedly, I wrote an article several years ago discussing *Moneyball* and its potential applications to the actuarial profession.) While the media and business books have popularized the potential uses of data with compelling narratives, they have not adequately highlighted the limitations associated with data analysis—particularly as it applies to complex models that attempt to predict future human behavior.

A simple comparison between predicting the average height in a large population and predicting the price movement in the stock market provides an extreme example of the problem. For example, If we have physical data on a large number of Americans (including height, weight, and demographic data), we have a number of statistical techniques that would allow us to accurately predict the height of another large population. In this case, the data analysis works largely because we are predicting a biological attribute that is more limited and less complex. The price movement in the stock market, on the other hand, is driven by a wide range of factors that make prediction and the deployment of mathematical models much more difficult. One only needs to look at the hubris of many technical analysts who have attempted and ultimately failed to predict future stock market movements. As chronicled in the book *When Genius Failed*, the catastrophic failure of the Long Term Capital Management hedge fund and their two Nobel Prize winning economist advisors provides a clear example of this problem.

ULTIMATELY, THE BASIS OF OUR WORK DEPENDS ON APPLYING SOPHISTICATED STATISTICAL TECHNIQUES TO HISTORICAL DATA TO MAKE PREDICTIONS ABOUT THE FUTURE.

The above example highlights the problem associated with worshipping data analysis in all situations. While it is absolutely appropriate to use and expect significant prediction power in some situations (predicting height in a population, quantifying the value of baseball players, segmenting credit card customers), assuming that this approach will be equally effective in predicting more complex models is simply not appropriate. In saying this, I'm not suggesting that models or analysis should not be employed, but I am suggesting that the analysis should clearly highlight the prediction limitation and the potential for a wide range of factors to impact results. As I will highlight in the last section, I also believe that business decisions dependent on complex environments should be more holistic and less dependent on the simple results from a model.

Environmental Change

Ultimately, the basis of our work depends on applying sophisticated statistical techniques to historical data to make predictions about the future. To the extent historical data no longer accurately represents a given phenomenon—human behavior in utilizing services, for example—even the most sophisticated data analysis will not adequately predict the future. As a result, unless we can quantify this change in future behavior, the models built up using this historical data will inherently produce inaccurate predictions.

By most measures, we are now in an economic and regulatory environment that is much different than our historical experience. Considering the dislocation and severity of our economic challenges along with the enormous change in health care regulation, the historical data and experience is not sufficiently robust to account for all the factors that could impact human behavior. Although we still need to employ sophisticated modeling and attempt to quantify behavior in this new environment, we also need to acknowledge that our prediction accuracy will not be the same as our historical pricing accuracy.

Consistent with this, we need to provide quantitative and *qualitative* opinions of the potential distribution around an expected outcome. In addition to highlighting the potential variation, this process also helps maintain our reputation if an unforeseen event or change does occur.

A Proposed Response to the Problem

First and foremost, we need to approach data analysis with humility and a certain degree of skepticism when attempting to predict the future of complex systems (stock price changes, future GDP growth, election results, human behavior in utilizing services in an environment with significant economic change). We need to openly acknowledge that predicting the future is difficult and subject to an infinite number of unforeseen events and changes that could impact results. Consistent with this view, we also need to openly acknowledge the limits of our statistical predictions and provide both quantitative and qualitative analysis in outlining potential outcomes. As part of our qualitative discussion, we need to consider the broader business strategy and have a philosophy toward expected changes in human behavior. While this approach may run against the grain of those worshiping data and its potential to solve business questions, I believe this provides an honest appraisal of data and its implications that underpin our profession. This approach also helps maintain our credibility if an unforeseen event or change does occur that impacts our results.

In addition to acknowledging our limits, I also think that the most common pitfalls to data analysis need to be openly discussed including presenting data with almost no credibility, mistaking correlation with causation, biased data mining, the problems with developing a narrative bias, and presenting data without proper caveats.

In considering the challenges in our profession, I can't help but think of a famous quote from the economist Friedrich Hayek: "The curious task of economics is to demonstrate to men how little they really know about what they can imagine they can design." Like economists, in addition to making unbiased predictions about the future using actuarially sound statistical techniques, I also think our profession has an obligation to clearly articulate the limits and potential variation in our predictions of complex systems. ▼

(This article first appeared in the January 2012 issue of Health Watch. *It is reprinted here with permission).*

BOOK REVIEW

Growing Artificial Societies: *Social Science from the Bottom Up*, by Joshua M. Epstein and Robert Axtell

Reviewed by Ben Wolzenski

This engaging, easy-to-read book brings the concept of artificial societies to life. Step by step, *Growing* builds a demonstration that complex collective behavior and outcomes can evolve—or grow—in a model with very simple rules for its environment and the actions of its inhabitants, or "agents." How does this occur?

The "artificial society" of *Growing* is, of course, an agent-based model. (For a superb exposition of agent-based models in complexity science, see "Complexity Science: An introduction (and invitation) for actuaries" by Alan Mills, FSA, ND on the SOA website at *http://www.soa.org/files/research/projects/research-complexity-report.pdf*).

The environment—the Sugarscape—is a two-dimensional grid on which sugar "grows" to its capacity at each grid point. Initially, "agents" act based on a simple rule: go to the biggest mound of sugar you can see, gather it, and eat what your metabolism requires per time period.

Each agent has limited "vision" and "metabolism" randomly assigned with ranges. Even with no further features of abilities, this simplest version of Sugarscape produces an interesting variety of results—how agents migrate, how the size of populations vary, and how wealth (accumulated sugar) is distributed among agents when the basic parameters of sugar growth, agent vision and metabolism are altered.

Ben Wolzenski

Succeeding chapters define simple rules for seasons, pollution, sexual reproduction, cultural group membership and transmission, inheritance, combat, trade (with spice as a second commodity growing on the Sugarscape), disease transmission and immune response. For each addition of a simple rule, we see new phenomena—social, cultural and economic—in the emergent society. It is what the authors succinctly call "The Surprising Sufficiency of Simple Rules" to produce complex systems.

Actuaries deal with complex systems on a daily basis. Building artificial societies may give us a quite different tool for understanding them. One final note: by the time this article is printed, a session entitled, "Using an Artificial Society (a Complexity Science Tool) to Project Life Insurance Sales" will have been held at the 2012 Life & Annuity Symposium. Hopefully, more on this fascinating tool will follow. ▼

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BOOK REVIEW

Bad Science, by Ben Goldacre

Reviewed by Dave Snell

"There are three kinds of lies: lies, damned lies, and statistics."– Popularized by Mark Twain, who attributed it to the 19th-century British Prime Minister Benjamin Disraeli (1804–1881).

I want to start the review of *Bad Science*, by Ben Goldacre, with two warnings about it:

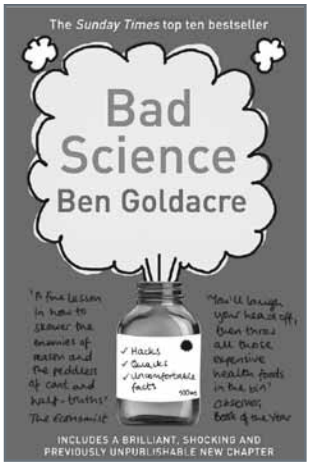
1. Language
2. Ideology

Regarding language, this book is written in English—not American English. I must admit that makes it a more difficult read until you get used to the many differences between the two languages. Having lived for a few years in Australia, I was familiar with common terms like the Vinnies (St. Vincent de Paul), the Salvos (Salvation Army), going to a physio (physical therapist) and a chemist (pharmacist). I was not familiar with some of the very common London phrases like the MMR Hoax. It was not referring to a British Enron or the salacious escapades of a movie star, but to the media's nine-year misguided campaign against use of the Measles, Mumps and Rubella vaccine. Plus, I had to look up some English words that are not common in my limited American vocabulary.

Regarding ideology, Ben Goldacre, M.D., is an iconoclast extraordinaire. He attacks widely held beliefs about the value of homeopathy, mega vitamin supplements and many alternative healing therapies. If you are big fan of any of these, you may find some of the material disturbing.

OK, so why do I recommend this book as "must reading" for actuaries who are involved in, or just interested in, predictive modeling, health insurance or statistical inferences?

I endorse *Bad Science* as a good primer on how clinical studies should and should not be conducted; and on how statistics are used and misused to manipulate public opinion. I have not seen such a memorable text on the subject of good and bad statistics since I read *The Nature of Statistics*, by W. Allen and Harry Roberts (1968) over four decades ago. That ancient paperback was once optional reading for the old probability and statistics actuarial exam and it was far more valuable to me than the required texts and study notes that focus on mathematical distributions and formula derivations.



Two anecdotal examples are still useful reminders to me that there is more to a statistical study than we sometimes assume. One example was a study that tried to determine the average family size at a large school. Each student was asked how many brothers and sisters he had. The resulting average was higher than expected; and the reason, of course, was that families of five children often got as many as five votes, while the single child family only had one vote. Sometimes we need to check for an inherent bias in our studies. Another was a story about a man who had a hearing problem, but could hear well if people spoke up more loudly. He could not afford an expensive hearing aid so he ran a wire from inside his shirt to a small piece of plastic he placed in one ear. Thereafter, he had few hearing problems because most people would notice the plastic and wire, assume he was hard of hearing, and speak louder for him. This introduced me to the psychological biasing impact of studies.

Bad Science is several steps beyond these simple examples and explains the basis of good experimental and statistical techniques; and also bad ones—those that yield inaccurate and misleading results. He gives us best practices for health studies, and then shows how special interests can distort the results from even well planned, double blind, randomized, statistically significant studies. He shows real world examples of how we are fooled into buying needless supplements, useless treatments, and counterproductive

Dave Snell

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medicines being pushed by the Big Pharma (pharmaceutical) companies.

A particularly disturbing chapter is a free one he included after the first edition of his book had already been published. This chapter was delayed because he was being sued at the time by a vitamin-pill entrepreneur. A link to the freely downloadable chapter, "The Doctor Will Sue You Now" is at *http://badscience.net/files/The-Doctor-Will-Sue-You-Now.pdf* and the short description of the suit is at *http://www.badscience.net/2008/09/matthias-rath-pulls-out-forced-to-pay-the-guardians-costs-i-think-this-means-i-win/*.

Dr. Goldacre is a medical doctor and a science writer who has the ability to educate and entertain at the same time (albeit in that sometimes bothersome dialect of English). He also addresses several commonly held, but incorrect, beliefs about clinical studies. For instance, some well-meaning consumer advocates say that giving placebos in trials is unethical—everyone should have the benefit of the improved medication. That, of course, assumes that the medication is better, which is what is being tested. We don't know the result of a trial until we actually perform it. Duh, that's why we do these experiments in the first place! Furthermore, the assumption is usually that the new medicine will be either better, or not better. Seldom do we consider the possibility it will be worse, or downright life threatening, like the painkiller Vioxx, which caused tens of thousands of heart attacks. As I am writing this review, a unit of Merck & Co., the second-largest U.S. drugmaker, pleaded guilty to a criminal misdemeanor charge as part of a $950 million settlement of a U.S. government probe of its illegal marketing of the painkiller Vioxx. Likewise, Thalidomide, which caused thousands of infant deformities, was not the ethical choice over a placebo. Current ethical side-by-side clinical trials involve giving the new treatment versus a placebo in situations where a placebo is warranted, or the new medicine (or treatment or procedure) versus the current best medicine (or treatment or procedure) where the illness or condition is one that requires treatment.

THE PURPOSE IN *BAD SCIENCE* IS NOT TO SUMMARIZE BEST PRACTICES IN CLINICAL STUDIES AND THEIR STATISTICAL INTERPRETATIONS. IT IS TO EXPOSE THE "BAD SCIENCE" TECHNIQUES BEING USED TO MISLEAD THE PUBLIC.

Placebos, however, are not as obvious as one might think. The author shows us that two pills are deemed better than one, capsules are better than pills, injections better than capsules, fancy packages better than plain ones, expensive placebos better than inexpensive ones, and that even color (or in his dialect, colour) can impact the results of the efficacy of the placebo.

Goldacre has an entire chapter on placebos, and I found it fascinating. Here is one example of the power they can have:

> "About a hundred years ago, these ethical issues were carefully documented by a thoughtful native Canadian Indian called Quesalid. Quesalid was a skeptic: he thought shammanism was bunk, that it only worked through belief, and he went undercover to investigate this idea. He found a shaman who was willing to take him on, and learned all the tricks of the trade, including the classic performance piece where the healer hides a tuft of down in his mouth, and then, sucking and heaving, right at the peak of his healing ritual, brings it up, covered in blood from where he has discreetly bitten his lip, and solemnly presents it to the onlookers as a pathological specimen, extracted from the body of the afflicted patient.
>
> Quesalid had proof of the fakery, he knew the trick as an insider, and was all set to expose those who carried

> it out; but as part of his training he had to do a bit of clinical work, and he was summoned by a family 'who had dreamed of him as their saviour' to see a patient in distress. He did the trick with the tuft and was appalled, humbled and amazed to find that his patient got better.
>
> Although he continued to maintain a healthy skepticism about most of his colleagues, Quesalid, to his own surprise perhaps, went on to have a long and productive career as a shaman." p.77

The purpose in *Bad Science* is not to summarize best practices in clinical studies and their statistical interpretations. It is to expose the "bad science" techniques being used to mislead the public. His anecdotal examples though give the best practice examples in a more memorable way than a list of bullet items in a study note.

For example, he explains in detail how the public came to accept the "fact" (never substantiated by any legitimate study) that fish oil pills will improve your child's intelligence. He then says, "Friends tell me that in some schools it is considered almost child neglect not to buy these capsules, and its impact on this generation of schoolchildren, reared on pills, will continue to bear rich fruit for all the industries, long after the fish-oil capsules have been forgotten."

But what if your audience is more sophisticated than the masses? What then can you do if you are dealing with academics or doctors who have been trained to notice obvious flaws such as "no blinding" or "inadequate randomization?" Then, you do what so many industry studies do: choose to study winners, compare against a useless control, use inadequate dosages of competing drugs, or use very high dosages of them to induce side effects. The list of tricks goes on, and Goldacre shows us many examples in real life.

He quotes noted physicist Richard Feynman who sarcastically marveled at the coincidence of seeing a car in the parking lot with the license plate ARW 357. "Can you imagine? Of all the millions of license plates in the state, what was the chance that I would see that particular one tonight?" Then, Goldacre gives us a cardinal rule of any research involving statistics: "you cannot find your hypothesis in your results."

> "Imagine I am standing near a large wooden barn with an enormous machine gun. I place a blindfold over my eyes and—laughing maniacally—I fire off many thousands and thousands of bullets into the side of the barn. I then drop my gun, walk over to the wall, examine it closely for some time, all over, pacing up and down. I find one spot where there are three bullet holes close to each other, then draw a target around them, announcing proudly that I am an excellent marksman." p. 275

I am so tempted to add many more quotes from the book. Goldacre has taught me, through the absurd stories of actual events, how easy it is to mistake coincidence for causality; or to distort a result without changing any of the facts; or to implant in the public minds a truth which does not exist.

Bad Science is a good book for actuaries to read. ▼

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