SOCIETY OF ACTUARIES Forecasting and Futurism Section

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Forecasting & Futurism

NEWSLETTER

Genetic Algorithms—Useful, Fun and Easy!

By Dave Snell

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Forecasting & Futurism

NEWSLETTER

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FROM THE EDITOR:

Sugar and Spice, and Everything Nice!

By Dave Snell

Welcome to another tasty sampler of Forecasting & Futurism (F&F) topics.

I am part of a generation that has fond memories of many Bob Dylan songs; and I was thrilled to read "The Times They Are A-Changin'" from our incoming chair, Clark Ramsey. Clark describes some of the major ways our world is changing and he relates these changing times to the many innovative initiatives underway in the F&F Section. This issue is packed with some exciting new techniques to help embrace the amazingly expanded toolkit available to actuaries today.

Ben Wolzenski shares his recent introduction to artificial societies. I first saw a demonstration of Sugarscape by Robert Axtell in early 2010 (as Ben tells in his article, it goes back to at least 1996), and it was fascinating to watch; but at that time we didn't have an easily accessible insurance application for us to try it out in our world. Ben modified the online model and created one to simulate purchases of life insurance. He summarizes his learning curve and his enthusiasm in the article, "Artificial Society Modeling with Sugarscape." In the vernacular of my grandkids, this simulation stuff is sweet!

Brian Grossmiller gives us an overview of applied futurism in his article, "Futurism in the Workplace." Past F&F newsletter issues have had some in-depth explanations of Delphi study techniques; but Brian also describes cross-impact analysis, decision modeling, environmental scanning, a futures wheel, and gaming and simulation … and his list of topics goes on to tell us about genius forecasting, relevance trees, scenarios, system dynamics, trend impact analysis and visioning. It's like a candy store of new tools for us.

Some of you may have attended workshops that Brian and I conducted on genetic algorithms. Feedback from some participants said they enjoyed it; but that we covered so much in such a short amount of time that they

wanted a slower, more step-by-step, introduction to this powerful process. I have attempted to provide that in my article, "Genetic Algorithms—Useful, Fun and Easy," which starts with Genetics 0.01 and provides the thought process I followed to create a genetic algorithm to solve a health insurance problem far faster than I know how to do by other means. If you like it, this will become a series.

Another powerful tool being used now in the insurance industry is predictive modeling, and earlier this year we were shown a dramatic application of predictive modeling by the Target chain. They were sending baby-related coupons to a woman whose family had no idea she was pregnant! See the *Forbes* article on this at *http://www.forbes.com/sites/kashmirhill/2012/02/16/how-target-figured-out-a-teen-girl-was-pregnant-before-her-father-did/*. I was really pleased to get reprint permission from *On the Risk* magazine to share Mark Dion's excellent article, "Predictive Modeling, A Life Underwriter's Primer." Mark gives a summary of current usage,

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the conceptual process to build a predictive model, a description of several types of predictive models and an unbiased list of the advantages and disadvantages involved.

If you have been reading the literature on complexity science, you may have experienced some frustration that different authors give substantially different definitions of it. In fact, when I attended a workshop on complexity science (or complexity sciences—even the name was in dispute) at the Santa Fe Institute, the birthplace of it, these world leaders could not even agree on the definition. It's not surprising then that a roundtable of six F&F Section participants had some diversity of ideas and opinions. We have included the summary of this discussion (edited by Glenda Maki) for you in "What Is Complexity Science?"

That discussion typifies the importance of the theme of Min Deng's article, "Actuarial Communication at a University." Min's point is that without effective communication skills, we will be hampered in our attempts to get favorable actuarial and management reception to our ideas. She describes the situation where a student with no exams can sometimes get an internship while a student with two exams might not be offered one. Likewise, if we are to effectively promote the use of the new array of F&F techniques, we need to be able to explain what they are, where they are useful, how to use them, and how to evaluate answers from models that no longer are the result of a simple, easily replicable, formula.

Dave Snell

Just to add a bit of spice to the mix, we also have included an ad for the Speculative Fiction (SF) contest that we are again proud to co-sponsor. I was one of the judges for past SF entries and I enjoyed the creative stories submitted. I urge you to consider writing your own vision of the future. Cash prizes await the winners; and the deadline is not until Jan. 31, 2013. In a sense, though, everyone who enters is a winner. It's a great chance to indulge in describing the world as you want to see it. Check out the link *http://www.soa.org/Professional-Interests/speculative-fiction-contest.aspx* for more information.

I can't remember a previous issue where we had so many of the newer F&F techniques discussed. It truly is a candy store of ideas. Enjoy all of the articles and let us know what treats you want to see in future issues.▼

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FROM THE CHAIRPERSON:

The Times They Are A-Changin'

By Clark Ramsey

The words that the legendary Bob Dylan sang nearly a half century ago still strike a chord today: *The Times They Are A-Changin'*. Massive change is all around us in the world today: In an effort to fend off economic collapse and kindle recovery, we see the central banks of the United States, Europe and Japan engaging in new and largely untested monetary programs on a scale so vast that it would have been unthinkable just a few years ago. Whether they have removed tail risk or created it will only be knowable in retrospect, if at all. Across much of the Arab world we have seen dictators fall, and it is not at all clear yet what this portends for the citizens of those countries or, more broadly, for international relations. A historic leadership transition will soon take place in China as the "Fifth Generation" takes power. In the United States, the November elections will have been decided by the time you read this. Looking over a longer horizon, the demographics of most of the developed world, including China, are leading to an aging population and, presumably, creating strong headwinds that threaten to curtail economic growth.

Our actuarial world is certainly not immune to the rapid change swirling around us. The low interest rate environment that the central banks have engineered presents major issues to those with long-tail liabilities such as long-term care, payout annuities and pensions. The Society of Actuaries will offer a general insurance track in the near future, and the profession will be dealing with some new acronyms, such as IFRS, ORSA and ACA.

Given this changing environment, it is an opportune time for actuaries to expand their toolbox by adding forecasting and futurism techniques, which of course is exactly what your Forecasting & Futurism Section endeavors to provide.

With that as prologue, I welcome you to another exciting issue of the *Forecasting & Futurism Section Newsletter*. Our current plan is to provide you with two newsletters a year. This issue covers genetic algorithms, predictive modeling, artificial society modeling and actuarial communication at university. That is a pretty broad range of

topics! If there are other topics you would like to see in a future newsletter, please feel free to contact our newsletter editor, Dave Snell, or me with your ideas.

Your section made considerable progress during 2012 thanks to the volunteer efforts of the section council and of the friends of the council. Our membership continued to grow, making us one of the very few SOA sections to expand over each of the last two years. We also sponsored or co-sponsored sessions at the health meeting, the annual meeting, the Life & Annuity Symposium and, for the first time, at the Valuation Actuary Symposium. These sessions covered an impressive breadth of topics: Complexity science, applied futurism, the Delphi method, demographics, genetic algorithms, generalized linear models and regression/time series methods.

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Clark Ramsey

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Several council members and friends of the council participated in a blog roundtable discussion on complexity science, and we have included a summary here in this issue for you. It was an interesting discussion and in a nontechnical manner provides some background on and insight into complexity science.

We also put on a webcast on genetic algorithms, creating an educational opportunity for those who were not able to attend one of the sessions at earlier meetings. Our intention is to sponsor another webcast in 2013, and we will also explore the use of podcasts to help us reach a broader actuarial audience in our effort to promote the tools and methods used in forecasting and futurism.

In addition to sessions at SOA meetings, a blog and the webcast, we co-sponsored the Speculative Fiction contest, the Actuarial Research Conference, and the first Long-Term Financial Planning Summit. The Long-Term Financial Planning Summit provided a sobering look at why the level of expected returns that are often being assumed in actuarial work may prove optimistic. Donald Krouse and I represented the section at the summit, and Donald has an article on it in the July 2012 newsletter that is well worth reading if you haven't already done so. In 2012 we again sponsored a forecasting contest with an iPad for a prize, focusing this year on forecasting the unemployment rate.

We have also seen change in your section council as part of the annual election cycle. Please join me in welcoming the three newest members of the section council: Doug Norris, Dave Snell and Richard Xu, who were elected to the council in September. Dave is returning to the council again after a one-year absence during which he continued to act as our newsletter editor and also spoke at several SOA meetings on section topics such as complexity science and genetic algorithms. Doug and Richard both also presented at sessions sponsored by the Forecasting & Futurism Section at SOA meetings in 2012. Each of our new council members has a lot to contribute to the section, and I am looking forward to working with them.

I would also like to thank our outgoing council members, Min Deng, Jon Deuchler and Mike Lindstrom for their efforts. Mike served as our secretary/treasurer, co-research coordinator and Web page coordinator; Min as our education coordinator, and Jon as our co-research coordinator. It is my sincere hope that they will continue to contribute as friends of the council. Finally, our section continued to thrive during the past year under the chairmanship of Donald Krouse, who will remain on the council for another year.

Enjoy your newsletter, and as always I welcome your thoughts and suggestions on how to improve the section. Feel free to contact me or any of the council members and let us know how we can make your section more valuable to you. We will continue to strive to better provide you with an expanded and improved set of actuarial tools, because *The Times They Are A-Changin'*. ▼

Genetic Algorithms—Useful, Fun and Easy!

By Dave Snell

I like genetic algorithms; and I want to show you how cool they are and how you can make your own. Genetic algorithms are techniques we can use to solve some problems that we do not know how to solve deterministically. They utilize methods that bear a strong similarity to the evolutionary process; and they leverage the capabilities of computers in order to simulate the progress of thousands of generations in a relatively short amount of time.

In this article, the first of a series, I'll make some simplifying assumptions since the topic of genetics is complex and no one on earth has a perfectly clear understanding of it. New genetic discoveries occur every day. Daily we find out that something previously assumed was not correct, or not always correct depending on the circumstances. However, that's OK for our purposes because, like the simple little creatures I'll discuss today, we too are continually evolving and learning.

BACKGROUND GENETICS

I have found it useful to learn some basics of genetics to provide a reference to draw upon for some ideas to get myself over hurdles in my creative thought process. When I ran into a performance problem it was handy to be able to step back and ask myself, "How did nature do that?" In fact, a new set of problem-solving techniques has emerged based on nature. One book I read a couple years ago, *Nature-Inspired Metaheuristic Algorithms*[1] went into great detail explaining Ant Colony Optimizations, Bee-Inspired Algorithms, Swarm Optimization, Firefly Algorithms, Bat Algorithms and even Cuckoo Searches. Not every good idea has to come from an actuarial study note!

We each have approximately 10 trillion human cells (give or take a trillion or so; but who's counting?). You might be surprised to know that our human cells are outnumbered about 10 to 1 by bacteria cells; and without them we could not survive.[2] In total, these bacteria cells, although smaller than human cells, weigh about a kilogram; and although dispersed throughout the body, they represent the equivalent of another major organ.

Our DNA is like a blueprint, or template. It dictates how proteins will be made; and proteins are the machines of the body. The blueprint is used to make exact copies of the cell for replenishment and growth, and to make hereditary contributions to children during sexual reproduction. The details go way beyond the scope of this article (or of my knowledge of genetics).

Cells die and are replaced throughout our lifetime. Most of the time, the copies made are exact copies of the original cell. This is the end result of a cell division process called **mitosis**,[3] where a cell splits into two identical cells. **Meiosis**, on the other hand, is the cell division process where four haploid cells or "half-cells" are produced. Sexual reproduction involves the joining of two haploid cells from different organisms. During sexual reproduction we pass some of our DNA to our children, and both parents contribute. Genetic algorithms borrow from both of these concepts to produce better and better solution sets.

One more factor in the cell replication process is **mutations**. In nature, successful mutations are very rare. The Tibetan tolerance for high altitudes is one example; but the

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NEW WORDS TO LEARN

Mitosis results in a cell splitting into two identical cells.
Meiosis results in a cell splitting into four "half cells."
Mutations are random changes due to noise or some other factor during the mitosis or meiosis process.
Alleles result in physical or behavioral trait differences among us.
Genes are units of heredity among us.
Genome is the term we use for the set of gene codes and non-coded information in our DNA/RNA strings.
Elites are the actors (bots, robots, creatures, etc.) who live into the next generation via mitosis.
Inbreeding is a condition where the gene pool becomes too similar. It is a danger in nature and in our algorithms. It stifles new progress.

Dave Snell

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overwhelming majority of mutations die within a few days of the mitosis or meiosis process.

An **allele** is any of several forms of a gene, usually arising through mutation, that are responsible for hereditary variation. The alleles result in trait differences among us. Traits can be physical or behavioral; a physical trait example is eye color (not counting colored contacts!) and a behavioral trait example is the Golden Retriever's impulse to chase and fetch a thrown stick or Frisbee. Some traits may seem to have elements of both. Roughly one-fourth of the population has "Hitchhiker's thumb" (like mine, shown on the right) while the others have a straight thumb (like my associate's on the left). Perhaps I might also be more inclined to gesture for rides than my associate who would have to place his thumb in a less natural position to be a stylistically correct hitchhiker. *"Thumbs up for genetics!"*

Figure 1: Straight Thumb

Figure 2: Hitchhiker's Thumb

Take heart! All you need to know about traits for now is that children inherit them from their parents (along with the occasional mutation).

The **genome** is the entirety of an organism's hereditary information. It is encoded either in DNA or, for many types of virus, in RNA. The genome includes both the genes and the non-coding sequences of the DNA/RNA. Some of the non-coding sequences of our DNA, the 98 percent previously thought to be junk DNA, may contain, among other things, the programming mechanism that operates upon the 2 percent we have identified as **genes**.[4] Frankly, we do not know much about what is in that 98 percent, nor do we know why some lower order creatures have longer genomes than we do. But in our algorithms we can make our genomes as long (or as short) as we wish, to fit our problem.

The bulk of our lifespan is spent in mitosis. Cells die on a regular basis and are replaced by exact copies. In some respects it's a boring process; but it helps us to avoid growing additional appendages or other such surprises as we age. I mentioned that mutations are rare. That's because our genomes, in the non-coding section, contain special molecular switches that keep watch over the mitosis and meiosis processes and try to dispose of cells that are not exact copies of the original.[5] These rogue cells are mutants; and generally they are not tolerated. A small percentage of them do survive. When the molecular switches themselves are damaged or inaccurately copied, the result is sometimes that this oversight process is disrupted and diseased cells proliferate or fail to self-destruct. Cancer cells seem to be cells without an adequate oversight process.[6]

GENETIC ALGORITHMS

As stated earlier, genetic algorithms are techniques we can use to solve some problems that we do not know how to solve deterministically. They are not a panacea for all problem solutions; but they can be very useful for problems that exhibit the following characteristics:

1. There is no direct deterministic solution known; or, if there is, it is prohibitively difficult to implement in real time.
2. The number of possible solution sets is very large—too large to try them all in the desired time frame.
3. We can devise a sufficient scoring system or ranking scheme to quickly compare the relative value of any two possible solutions.

Note that I have repeated a theme here regarding time: Even if an exact formula is known, it takes too long to employ it. The number of answers is too large to check them all in time. The time to compare two possible solutions is acceptably short. Time was a major consideration for John Holland; he is generally thought to be the father of genetic algorithms. In 1975 he wrote the book, *Adaptation in Natural and Artificial Systems*,[7] which launched the study of them. Holland was fascinated by the speed of evolution; the incredible progress made in a relatively short time in the fossil record suggested to him that nature had processes worthy of study by computer scientists.

Holland developed a fitness function based upon alleles, and he also tended to focus on chromosomes[8] more than individual genes; but for our purposes, I am using an analogy of only gene strings just to try to keep things simple.

AN INSURANCE EXAMPLE

OK, you have suffered through enough background theory for now. Let's apply what we have learned so far with an insurance example.

Brian Grossmiller, a friend of mine from the Forecasting & Futurism Council, is a health insurance actuary—a very creative one. We sometimes team up to co-present a workshop on genetic algorithms; and he posed a problem to me of how to optimize the choice of provider groups for a health network.

Note: You can go to the F&F site *http://www.soa.org/professional-interests/futurism/fut-detail.aspx* to download an Excel workbook containing the 3,304 providers and the code containing a genetic algorithm solution.

Let's assume a geographic area has 3,304 provider groups with a total of 12,881 providers working through them. A provider, for our purposes, would be a doctor, physical therapist, etc., and a provider group might have one or several providers. Each provider group would cover one or more specialties. Each group has its own relative cost, based on empirical data, and each group may have as few as one specialty service, such as acupuncture, or many of the 37 specialties we have included in our example. The overall network of provider groups that you choose must meet a minimum vector of coverage availability as determined by your target member population size.

In this example, we want at least five providers for every specialty and at least 20 for the primary care specialties such as family practice. There is nothing magical about these numbers. You can change them any way you wish. Brian made the comparison process easier by normalizing his workbook so that the fitness function (in this case, his relative cost) would be 1.00 if all of the providers were included in the network. That becomes our baseline for scoring.

Figure 3: Intuitive Solution to a Small Subset of the Problem

Health System	Relative Cost	Total Providers	Mental Health Counselor	Psychiatry	Chiropractic	Ambulatory Surgical Center	Pathology
Group # 1	0.93053	1	1	0	0	0	0
Group # 2	0.59494	3	2	0	**1**	0	0
Group # 3	1.46132	3	1	0	0	1	1
Group # 4	1.0883	1	1	0	0	0	0
Group # 5	0.53197	1	0	**1**	0	0	0

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Figure 3 on page 9 shows a very small portion of the hypothetical table. Please keep in mind that the actual spreadsheet shows 3,304 provider groups, 12,881 providers and 37 specialties. Each provider group and each specialty has been assigned an empirical relative cost (as part of the normalization process).[9]

Let's look at Group #2. This facility offers chiropractic and one other type of service (not shown), and overall, its previous billings have been far below the average for the entire network of all providers (only 59 percent of the average). Group #3 offers three specialties (mental health counselor, ambulatory surgery center and pathology), but its costs tend to be a lot higher than the average (a little more than 46 percent higher than the average).

If our challenge were to supply at least one psychiatry provider and one chiropractic provider, this would be an easy task. We could build a network of just Group #2 and Group #5. This would cover our needs (with a bonus of two mental health counselors included) and still have a relative cost far less than 1.00 so no further analysis would be needed. We can see the solution. It is actuarially intuitive.

Alas, reality often messes up our simple modeling view with lots of data (thousands of potential providers, dozens of specialties, clinics covering multiple specialties, relative costs by specialty and by provider group, relative quality ratings, etc.) and soon our view is looking less simple. Let's evaluate the three characteristics I specified.

1. **No direct solution**—We no longer have a simple, deterministic solution. It's become a messy problem. Plus, if you did figure out a formula to solve this, it would probably require a major revision once another criterion is added or whenever a new provider group opens a practice in the area, clinics or hospital systems merge, or a specialist is added to an existing clinic.
2. **Lots of possible solution sets**—A provider group is either in the network, or not in it, so our action set consists of only two possibilities for each provider. There are 3,304 provider groups, so the number of possible solution sets is $2^{3,304}$. That's a very big number. In fact, it is incomprehensibly big. It far exceeds the number of seconds since the big bang (10^{17}) and the number of atoms in the known universe (10^{82}). It far exceeds the number of atoms times the number of seconds! Clearly, an exhaustive solution is not an option.[10]
3. **Quick and easy scoring mechanism—**Ah, the wonders of Excel in the hands of Brian! He built in a simple summary area that gives the score for any particular solution set (see Figure 4).

Figure 4: Portion of Solution Sheet

	A	B	C
1	Genetic Algorithm Presentation		
2	Provider Network Fitness Function		
3			
4		Estimated Number of Members:	10,000
5			
6		Count of Contracts Used:	1,587
7		Included Providers:	5,045
8		Relativity to Overall Network:	0.7947
9		Adequate Network:	Yes

Brian's workbook computes a simple relativity score (in cell C8) that we can use to compare solution sets. Lower numbers are better than higher ones. If all providers were chosen in the solution set, the relativity score would be 1.000.

My three criteria are satisfied. This seems like a good application for a genetic algorithm.

THE LOGISTICS OF A GENETIC ALGORITHM SOLUTION

OK, we have reached the fun part. Now, we get to start our genetic algorithm solution to Brian's problem. You can find my VBA (Visual Basic for Applications) program code in the Excel workbook; but I urge you to first go through the conceptual development here before looking at the code. Once you understand the concepts, you can choose to use any programming language you wish.

Let's start with a generation. Oops! A generation of what? We get to decide what is appropriate to the situation. For this problem, any particular solution will have some subset of the available provider groups; and a provider group is either in or out of the network (no partials allowed). Actually, this suggests a very simple gene string. We can have a string of length 3,304 (our actual number of available provider groups) and each position in the string will be a zero (not in the network) or a one (in the network). Different authors may call this string a robot, a bot, an actor, or whatever. It is going to represent the "creature" we will be evolving. It could even be called a politician; but let's assume we want to end up with more intelligence than that and call our creature a set (short for provider group set).

We will start out with 100 sets.[11] Each one of them will have a gene string of 3,304 genes, and each gene can be only a zero or a one. Our first step will be to randomly assign zeros and ones to all of the genes in every set. In Excel, on a worksheet for the generation, we could put each set in a different column and then each row would hold the gene for that column. If set #5 had a gene string that started as 1001101 … that would mean it contains provider groups 1 (but not 2 or 3), 4, 5 (but not 6) and 7 …

Figure 5: Portion of Provider List Sheet

	C	D	E	F	G	H	I	J	K	
1										
2										
3										
4										
5								Chiropractic	Pathology	Card
6	Copy your solution set here and let						Cost	0.99	0.91	
7	the Excel workbook calculate the						Count Minimum	5	5	
8	resulting score.						Current Count	384	67	
9								738	161	
10		Total								
11				100%	0%	0%		1	2	
12	Health System	Inclusion	Relative Sco	Relative Cost	Relative Qu	Relative Referral Score	Total Provider	Chiropractic	Pathology	Card
13	Provider # 1	1	0.93	0.93	1.01	1.14	1	1	0	
14	Provider # 2	0	1.11	1.11	1.12	1.11	7	7	0	
15	Provider # 3	0	1.37	1.37	1.30	0.76	2	0	2	

Now, we can systematically copy a set at a time into column D of Brian's "Provider List" sheet (Figure 5) and read the resultant score from cell C8 of his "Solution" sheet (see Figure 4 on page 10). We save each of these scores so we can compare them by sorting from lowest (i.e., best) score to highest (worst) score.

If we do that, we may end up with some scores like this:
Set 1: 0.93 (best set of generation 1)
Set 2: 1.11
Set 3: 1.37
…

This is probably not that impressive. That's OK; we are just getting started.

Next, we'll decide upon some way to determine mating rights so that we can use these sets to spawn a new, hopefully smarter, next generation. Oh, that word "hopefully" is bothersome, isn't it? We don't want to risk our next generation being dumber; but if all we do is combine randomly created sets together—even the brighter ones—we could get bad combinations and our "spe-

Figure 6: Dave Joins the Mob

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cies" might devolve instead of evolve. Remember when I said that knowing something about actual genetics can be helpful? How does nature handle this?

In nature, the various members of a generation do not all live the same length of time. In essence, some die young and never get to have children; some have children and then die (perhaps even in childbirth); and some live on to coexist with the new kids on the block. In genetic algorithms, we call these latter ones "elites." In order to guarantee that our generations do not get dumber instead of smarter, we will specify that a certain number of the sets in generation 1 (the favored ones) will self-replicate into generation 2.

For now, let's set the percentage of elites to 10 percent. That means when we get around to building generation 2 from generation 1, the top 10 sets (of our 100 sets) of generation 1 will copy over exactly via mitosis. Our next task then is to figure out how to generate the remaining 90 sets of the new generation 2.

Figure 7: Meiosis—Two Parents (Set 2 and Set 5)

	Gene 1	Gene 2	Gene 3	…	Gene 2,500	Gene 2,501	…
Set 2	1	1	0	…	0	1	…
Set 5	0	1	1	…	1	0	…
Child	1	1	1	…	0	1	…
Source	Set 2	Set 5	Set 5		Set 2	Set 2	

Again, let's look at what happens in genetics. In most species of mammals, the biggest, or prettiest, or smartest, or strongest member or members of the group are deemed the most attractive mates for reproduction. In Figure 6 on page 11, I am conversing with a mob of kangaroos. The norm in a kangaroo mob is that only the dominant male of the entire mob gets to mate with the various females. Among humans, we are not quite that strict (although in history, emperors and kings had many, many mates) and most folks have a chance at finding a mate; but still the smartest, richest, strongest or prettiest seem to have more choices.[12]

We will arbitrarily say that the top 20 percent of the sets will be the parents of the next generation. This will, of course, include our elites (our top 10 percent). I have to emphasize that these percentages are not scientifically determined and this is not the usual method I would employ; but it works fine for this example, and it shows that there is still a lot of "art" in the making of genetic algorithms.[13]

Now that we have established our pool of potentially preferred parents (an alliterative approach to genetic algorithms), we can address the actual reproduction process. In nature, a child gets a DNA string that is composed of pieces from two parents. Let's say that we choose sets 2 and 5 as the parents. Then, on a gene-by-gene basis, each gene of the child will have either a copy of the corresponding gene from set 2 or the corresponding gene from set 5. The child will end up as some combination of sets 2 and 5 (see Figure 7).

OK, that works. However, we are limiting our possibilities here because of our experience. When Ben Wadsley, another genetic algorithm cohort of mine, wrote an asset-liability management genetic algorithm he got faster results by drawing from five parents rather than two. Once I thought more about this, I remembered that when we lived in Northern California, my older daughter once brought home her date, and he was surprised to discover that she had only two parents … and they were still married … and to each other! Clearly, I was naïve in assuming that we had to limit our genetic algorithms in this manner. In this example, we'll draw from our top 20 percent and let any one of the 20 of them be the dominant parent (gene contributor) for any gene in the child's gene string. This will provide a far better level of diversity, and our generations will continue to improve for a far longer time. Once I switched from two potential parents per child to 20 or more, I got a lot more diversity much sooner. Perhaps it does take a village.

ONCE I SWITCHED FROM TWO POTENTIAL PARENTS PER CHILD TO 20 OR MORE, I GOT A LOT MORE DIVERSITY MUCH SOONER.

Remember, inbreeding is bad among humans; and it is also bad in genetic algorithms. We want to keep the gene pool as diverse as we reasonably can in order to avoid marrying first cousins. Once again, I go back to genetics and see that a built-in mechanism exists to adapt to changing circumstances and add diversity. It's called mutation. Sometimes (perhaps most of the time) mutations result in a weaker cell; but sometimes it is an improvement. Some bacteria have developed the ability to mutate rapidly and thereby build immunity to antibiotics. We will generate our children as usual, and then randomly mutate some genes in the string. Assume we set our mutation rate to alter 30 genes of the 3,304. Again, play around with these parameters. You can learn (as do your genetic algorithms) through experimentation.

Figure 8 shows a revised picture of how the genes might be populated from five parents:

Figure 8: Meiosis—Five Parents (Our runs actually used more parents.)

	Gene 1	Gene 2	Gene 3	...	Gene 2,500	Gene 2,501	...
Set 1	0	1	0	...	1	0	
Set 2	1	1	0	...	0	1	...
Set 3	1	0	0	...	1	1	...
Set 4	1	0	0	...	0	1	...
Set 5	0	1	1	...	1	0	...
Child	0	0	0	...	1	1	...
Source	Set 1	Set 3	Set 4		Set 1	Set 2	

After we build all the sets for generation 2 (total = elites + children: 100 = 10 + 90), we repeat our test runs with this new generation and sort the scores again. Then, we repeat the process for many generations and watch as our "best set" results get better and better numbers.

In my first set of runs, I was getting down to 0.25, which was a vast improvement over 1.00. These results seemed almost too good to be true. They were.

There was a major flaw in my early logic. Do you see it? The flaw was that the score got better and better as we eliminated expensive provider groups; but I was not checking to make sure that the provider group sets provided adequate coverage! When you remove that requirement, this becomes a simple solution; but not an acceptable solution. I mention this because here we can easily say that the sets must satisfy the adequacy requirement or they don't count; but that runs the risk of having too few eligible sets. Consider the Royals. When they did not have enough diversity in their gene pool, they began exhibiting genetic disorders (e.g., hemophilia). We want to guard against complete exclusion of sets to the point where we become inbred.

My solution was to make the adequacy check a part of the scoring process and to add a number (I arbitrarily chose 100) to the result if the set did not provide adequate coverage. As the algorithm is set up to prefer lower scores, this will ensure that inadequate networks are severely disadvantaged for selection. Now, we can add as many additional criteria as we wish and still be assured that each generation will have a spectrum of better to worse results, and every generation can still retain 100 set members.

Our final genetic algorithm ran for several hundred generations and stopped improving once the scores got down to around 0.74, which can represent a significant cost savings over the original set of all available providers.

Let's summarize what we did:

1. We chose a gene string of length 3,304 where each gene had to be zero or one. This was a model for the 3,304 provider groups and the fact that each group could be in or out of the network.
2. We formed generation 1 by randomly assigning zeros and ones throughout each set; and we decided to have 100 sets per generation.
3. We tested each set of the generation and saved its score (penalizing, but not eliminating, any set that did not meet our coverage adequacy requirement).
4. We ranked the scores in order from best to worst.
5. We chose the top 10 sets and designated them as elites. Elites get to advance to the next generation intact.

CONTINUED ON **PAGE 14**

GENETIC ALGORITHMS … | FROM PAGE 13

6. We chose to have 20 parents per child, and we built the 90 children (to fill out the next generation) from pieces of the top-scoring 20 sets.
7. Each gene was chosen from some corresponding gene of one of the 20 parents (randomly choosing the dominant parent for that gene).
8. We went back through the children and randomly mutated 30 of the 3,304 genes (but we did not mutate genes of the elites).
9. We repeated steps 3 through 8 until the scores stopped improving.
10. We went out and partied while the genetic algorithm did all the grunt work for us; meanwhile the theoretical purist actuaries worked through the night trying to come up with a deterministic solution at our top competitor; and thousands of monkeys at typewriters tried to pound out the exhaustive best solutions at our not-quite-top-competitor.

The potential for genetic algorithms is amazing. One might even build a better species like this—oops, perhaps somebody did that!

Please download the Excel workbook and try out the algorithm. You can vary the assumptions and improve it in many ways. We built this as a learning tool for you. Brian Grossmiller, Ben Wadsley and I have conducted several workshops and presentations on genetic algorithms because we discovered that they are a very useful tool that, so far, has been underutilized by actuaries. In this article, I have described a simple (I hope) genetic algorithm that can have significant business value. Ironically, it is the least sophisticated of the genetic algorithms I have developed for these presentations. In future articles I'd like to share how we can extend these concepts to gene strings where each gene can take on multiple values (rather than just zero or one), where groups of genes (like chromosomes) can interact to produce special traits, where we impose multiple criteria with differing priorities, where the non-coding parts of the genome can be utilized, and where the sets (or actors or creatures or robots) can change actions based upon their ambient conditions, and even interact (compete for scarce resources, or cooperate and form alliances) with each other. The potential is exciting!

I wrote up front that I like genetic algorithms; and I want to show you how cool they are and how you can make your own. Please let me know if I succeeded (or how I should improve this tutorial for others).

Next time, we'll do some more sophisticated applications. ▼

END NOTES

[1] *Nature-Inspired Metaheuristic Algorithms,* Second Edition by Xin-She Yang, 2010, Luniver Press, Cambridge, UK.

[2] "The Ultimate Social Network," by Jennifer Ackerman, *Scientific American,* June 2012, p. 20.

[3] By definition, mitosis and meiosis are cell divisions. Mitosis is the cell division resulting in two cells identical to the parent cell—being identical, they have the same amount of genetic information. Meiosis is the cell division result in four haploid (or "half cells") with half as much genetic material as the parent cell. Mitosis and meiosis themselves don't imply reproduction of an organism in the biological sense, but rather the reproduction of cells. While this could be a whole organism (like many single-celled organisms in mitosis), it does not have to be. Meiosis simply means that you get four half-cells after cell division, but implies nothing about two half-cells coming together to produce another organism. Mitosis and meiosis each occur within a single organism. The joining of two haploid cells from different organisms (parents) is a separate part of sexual reproduction that occurs after the cell division (meiosis).

[4] "Journey to the Genetic Interior, interview with Ewan Birney," by Stephen Hall, *Scientific American*, October 2012, p. 72.

[5] The ENCODE project, sponsored by the National Institutes of Health, is revealing more of the functionality of the 98 percent of the human genome formerly described as "Junk DNA." See *http://www.npr.org/blogs/health/2012/09/05/160599136/scientists-unveil-google-maps-for-human-genome?ft=1&f=1128&sc=tw* for a short description of project findings.

[6] "Quiet Little Traitors," by David Stipp, *Scientific American,* August 2012, p. 68.

END NOTES CONT.

[7] *Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence (Complex Adaptive Systems),* by John Holland, Ph.D., 1992, The MIT Press, Cambridge, Mass. (first edition published by University of Michigan, 1975). John H. Holland is professor of Psychology and professor of Electrical Engineering and Computer Science at the University of Michigan. He is also Maxwell Professor at the Santa Fe Institute and is director of the University of Michigan/Santa Fe Institute Advanced Research Program.

[8] A chromosome is a single piece of coiled DNA containing many genes, regulatory elements and other nucleotide sequences. In the human genome, during the meiosis process, our DNA strand breaks up into 46 chromosomes (visible under a suitably powerful microscope). Again, I am oversimplifying by not bringing in a more thorough treatment of chromosomes; but for our purposes we can work with genes as though they are suitable surrogates.

[9] The relative cost of each specialty is not shown in this diagram. However, the workbook shows relative costs for quality, referral scores, etc. You may wish to incorporate relative scores for location, office hours, or any of a host of other metrics.

[10] Current thought is that the Big Bang occurred around 14 billion years ago, which is a little over 10^{17} seconds. An interesting thread can be found at *http://answers.yahoo.com/question/index?qid=20080525070816AAaZAOU*. Likewise, the number of atoms in the observable universe is obviously not known precisely; but it is generally thought to be in the range of 10^{78} to 10^{82} *(http://www.universetoday.com/36302/atoms-in-the-universe/).*

[11] In a typical genetic algorithm application, you may decide to have thousands of sets per generation. I am choosing just 100 here to keep the example simple. The advantage of more sets per generation is a greater diversity and higher probability the smarter sets will be a lot smarter. The disadvantage is that your algorithm will run slower as you have to test every set in the generation before you see your comparative results. It also may be more difficult to hold this information in memory, which can result in a lot of slower, disk drive interaction.

[12] An excellent book about this concept is *The Red Queen*: *Sex and the Evolution of Human Nature,* by Matt Ridley (April 29, 2003), Penguin Books, Ltd.

[13] My earliest algorithms for mating rights would base the probability of being chosen as a parent on the absolute score the robot (or set) obtained. Thus, a robot getting a score twice as good as the next robot would have twice the chance of mating. This approach works well in early generations; but gradually leads to inbreeding. A better approach was to base mating probabilities on the relative score. In this case, the top scoring robot of 100 would have 100/99 times the probability of mating versus the second place robot, and 100/90 times the probability of the 10th place robot. Try different reproduction schemes to see what fits your particular applications.

Actuarial Communication at a University

By Min Deng and Guangwei Fan

Communication is the source of human civilization development. It contributes to our understanding of the nature of things. It reduces errors and friction. It helps us gain a common understanding. It helps to improve the work efficiency. It enables us to better resolve conflicts among humans—to solve problems and to achieve goals. It allows people to exchange experiences to create a better and more comprehensive world. Communication is an essential work skill. Everyone needs to learn to how to communicate; and those who become better communicators have a distinct advantage over those who do not learn the skill involved in communication.

The actuarial profession tends to attract students who are highly talented in mathematics. In order to help them achieve their potential in the business environment, the universities have to supplement the mathematics training with various forms of communications training. I'd like to summarize some of these skills for you, and explain how one university attempts to teach them.

Actuarial communication skill training at Maryville University includes written communication, oral communication, listening communication, team work communication and professional communication.

WRITTEN LANGUAGE COMMUNICATION

Written language is the basis of communication between people. It has a fairly persistent and widespread use. Written communication includes memos, reports, proposals, plans and project papers.

In addition to the English courses in writing essays, actuarial students at Maryville University will learn writing communication skills related to the actuarial profession through courses in their major.

Guangwei Fan

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Starting with the freshman calculus course, students are trained to write the mathematical solution with a clear statement of the question and the logic of the problem solving process. Students not only grasp the calculus concepts, but they can communicate and explain the thinking process to others. Assignments, examinations and presentations are used to reinforce the learning.

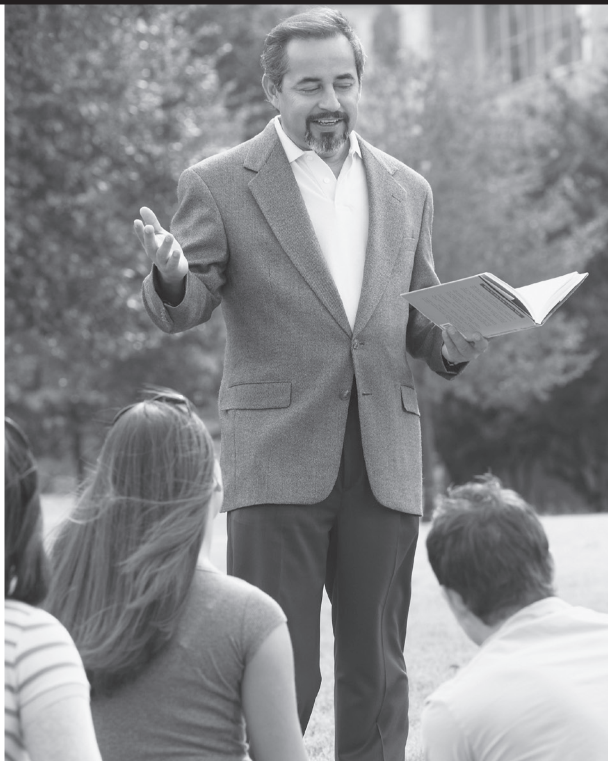
In the mathematical modeling with technology course, students are trained to write the Excel spreadsheets according to the standards of the actuarial profession and to meet the professional communication standards. Students are required to communicate the calculated results of their models using generally accepted principles in a consulting firm or an insurance company. The presentation of their model outcomes must meet both communication standards and actuarial standards as mandated by Actuarial Standards of Practice (ASOPs). ASOPs are promulgated by the Society of Actuaries (SOA). The students are trained to follow required documentation procedures that are applicable for all modeling and computer programming. For input sections of a model, the students are taught to provide input instructions using appropriate input menus, comments and data validations. Students are also required to write a paper each semester to improve their writing skills.

In statistics courses, students are trained to write as a part of the data analysis process. In statistical modeling courses, students can form a group of no more than three students to do projects. They meet to decide the topic, collect data, analyze data, and hand in final written projects.

In financial mathematics, students learn to write in teams. A team of three students will write project reports. In part I, each of them focuses on a different task of the project and then writes an individual report. In part II, the team gets together to write the report, integrating individual reports with a uniform style.

ORAL LANGUAGE COMMUNICATION

Oral communication is widely used because it can facilitate fast delivery and fast feedback. Popular forms of oral communication include interviews, meetings, speeches and presentations.



IN ACTUARIAL SEMINAR COURSES, STUDENTS ARE REQUIRED TO PREPARE THE PROBLEM SOLUTION TO PRESENT IN FRONT OF THE CLASS.

General speech courses are required in the freshman year. In actuarial seminar courses, students are required to prepare the problem solution to present in front of the class. In financial mathematics and actuarial modeling courses, students will give PowerPoint presentations to the class.

Students with actuarial internship positions can register for co-op education courses that require a final project report. At the beginning of every academic year, there is an internship presentation night. Students share the internship experience with each other.

ACTIVE LISTENING COMMUNICATION

Active listening is a very important communication skill. Here we concentrate on listening to the speaker, summarizing and synthesizing the information heard, and questioning to ensure we understand correctly.

Many professional actuaries are invited to be the guest lecturers for our actuarial science program. Topics cover introduction to actuarial communication, insurance and risks, capital management, financial statements, derivative markets, statistical modeling and actuarial valuations. In order to strengthen our connection with the actuarial profession, an actuarial practitioner is invited to the class so that the students can learn the real-world survival skills. We use the real projects to solve actual questions and issues in consulting firms and insurance companies. This helps the students to understand the actuarial profession. This also helps them to understand the coursework and apply the learned course knowledge to the real problems. The speakers not only give the talk from the perspective of a working professional, but also give very important suggestions. For example, actuaries from area firms come and speak on topics they work on; and they give practical examples from their own projects. This also allows our students the opportunity to learn about topics currently beyond the SOA study notes, such as complexity science and advanced statistical modeling.

ACTUARIAL PROFESSIONAL COMMUNICATION

Another important part of communications training helps prepare the students to seek employment. This includes resume preparation, interviewing skills and question approaches to help the student get the interview and then do well at it.

Communication skills play a very important role in finding a job. We have had students who could find an internship without passing any exam. Unfortunately, in earlier times, we also have had students unable to find an internship after passing two exams. The secret is communication. In order to improve job interview skills, our alumni provide mock interviews every year before career day. Our Career Office provides a guide to help our students write attractive resumes.

If you wish to become an actuary, you need to pass exams; but that is a minimum requirement. Good communication skills are of paramount importance in being a successful actuary. ▼

Min Deng

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Futurism in the Workplace

By Brian Grossmiller

The techniques of applied futurism can be quite useful to an actuary's practice, either to complement existing methods or in their own right. In this article I will review the 12 techniques exposited in the old Course 7 Study Note, "Applied Futurism: An Introduction for Actuaries," by Alan Mills, FSA, and Peter Bishop, Ph.D. (available on the Forecasting & Futurism Section's website).

Common to futurism methods is a reliance on "softer" skills such as intuition or expert opinion, rather than more traditional hard science approaches. Also, they focus less on arriving at a single "right" answer and more on looking at a plausible range of future states. A key advantage of this type of approach is that it allows for planning across a range of contingencies and perhaps more robust decision making.

DELPHI STUDY

When faced with a problem that is not conducive to a traditional model, such as a delineation of risks in a new market where you have no data or experience, an expert's opinion can be useful. In the same vein as the old adage, "Two heads are better than one," a Delphi study attempts to collect the opinions of many experts. A Delphi typically consists of several anonymous rounds of opinion gathering and feedback where a moderator provides summaries of the experts' opinions back to the group. After receiving the summary, experts are asked to revise their opinions in subsequent rounds; this can continue for a predetermined number of rounds or until the opinions stabilize.

Brian Grossmiller

The anonymous nature of the opinion gathering gets around issues with hierarchical structures, as people might be inclined to agree with their superiors. Also, people who are aggressive can dominate a roundtable discussion; having the opinions compiled by a moderator helps to remove this effect. Studies should have at least two rounds; if nobody changes their opinion, then further rounds may be unnecessary.

Clusters of opinions might be the end result of a Delphi study rather than a single answer. A key challenge of Delphi studies is that they are difficult to perform well, particularly in finding a motivated panel of experts or in constructing a questionnaire that will elicit well-thought-out responses. Additionally, they can take several weeks or months for studies with multiple rounds, which can limit applicability of this method to time-sensitive inquiries.

CROSS-IMPACT ANALYSIS

A cross-impact analysis attempts to gain insight into the end result impact that a sizable number of events might have on a system of interest. When considering how 10 or more events might impact an organization over several years, there is an awful lot to keep track of. A cross-impact analysis forms a matrix of the probabilities of each event occurring along with the pairwise conditional probabilities given each of the other events.

This matrix can be run through a large number of random trials, where the effective probabilities of events occurring change throughout the time frame depending on which other events have occurred. An evaluation of the output of the random trials provides an idea of what the long-term impact of all of the events together might be.

An interesting extension of this idea is to evaluate the impact of alternative courses of action that might change the probabilities of the events occurring. This method could then give an insight into the long-term downstream impacts of a particular decision. However, the results will directly depend on the estimated probabilities, and pairwise conditional probabilities can be difficult to determine with precision.

DECISION MODELING

Decision modeling is a technique where weights are assigned to various criteria with simple examples being

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Figure 1: Example Matrix for Decision Modeling

Criteria	Weight	Alternative 1	Alternative 2	Alternative 3
1	0.20	85	96	96
2	0.35	70	76	78
3	0.15	50	58	64
4	0.30	70	53	69
Overall Score		70	70.4	76.8
Normalized Score		0.97	0.97	1.06

costs and benefits. Weighting can be determined in several ways, such as using a survey or by examining past decisions. Note that these weights can change over time as personal or organizational preferences change. Once the weights are determined, a set of alternative courses of action can be evaluated according to the criteria and weighted into an overall score.

A simple example will illustrate how a decision model works (Figure 1). The overall score for each alternative is computed and then normalized to the average; thus scores above 1 are more desirable.

ENVIRONMENTAL SCANNING

In environmental scanning, literature and websites about peripheral systems are reviewed, and the results can be compiled into a database. Systems that are not directly involved in solving a particular problem are easy to ignore; however, these systems can have significant effects later on. The goal of environmental scanning in keeping track of these systems is to increase the lead time for reacting to changes. Organizations commonly monitor relevant bills in applicable legislative bodies, so this type of technique is probably already being used to some extent in most organizations.

The major pitfall of environmental scanning is analogous to an issue with Internet search engines. The literature reviewed might actually prove irrelevant to changes in the system of interest, or conversely important articles or updates might be missed. Maintaining an awareness of external systems can be very beneficial to an organization, especially if the alternative is to ignore them.

FUTURES WHEEL

A futures wheel is a cheap and quick method to start thinking about the potential impacts of an idea or event of interest. The wheel starts with this central idea and maps out the primary impacts of this idea. Once the major primary ideas have been listed, they are connected to the central idea by lines and are all connected by a circle. Each impact is then treated as a central idea and its primary impacts are then added to the diagram.

Figure 2 shows an example of the secondary impacts being generated from the primary impacts. The shape of the resulting picture obviously demonstrates why these are called futures wheels. Subsequent impacts are generated as further levels of the futures wheel. This can continue for several levels but can get messy. An important caveat to using a futures wheel is that the timing of events is not reflected in the diagram. Two primary impacts of an event might happen several months apart.

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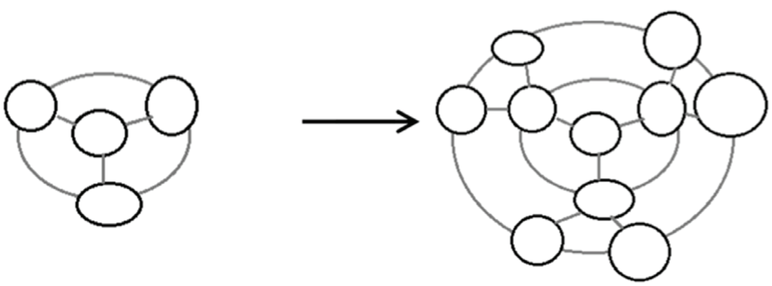
Figure 2: Development of Secondary Impacts in a Futures Wheel



GAMING AND SIMULATION

Gaming and simulation are typically used for training purposes; in the context of futurism they can be used to train people to react to uncertain future states. They rely upon a model of a system, so of course the effectiveness of such training will depend on how accurately the underlying model represents reality. In fact, utilizing an inaccurate simulation may be worse than nothing as it could train people to react incorrectly.

Use of a game or simulation can be much more engaging than reading a book and provides a fairly realistic way for personnel to practice a set of skills. These do tend to be enormously expensive to produce, which may prohibit constructing or adopting a simulation-based method for training.

Simulations can be an effective method of testing out various "what if?" scenarios. When faced with different options for a key assumption, a simulation can provide guidance as to the materiality of selecting one versus the other.

IN FACT, UTILIZING AN INACCURATE SIMULATION MAY BE WORSE THAN NOTHING AS IT COULD TRAIN PEOPLE TO REACT IINCORRECTLY.

GENIUS FORECASTING

Genius forecasting relies on the insight or intuition of a genius to make a prediction about the future. This can be a lot cheaper and faster than building a complicated computer model, but it does rely entirely on a genius's intuition.

It can be challenging to find a suitable genius to make a prediction as their expertise would need to be in a field relevant to the issue being forecast. Intuition can be developed through reading and by practicing making guesses about the future, though this can require significant time and effort.

RELEVANCE TREES

Relevance trees are a method of breaking down an issue or system into smaller component parts. The resulting tree looks like an organizational chart; the higher levels have fewer elements and are at a fairly broad level of detail. Lower levels in the tree are at a more granular level and have more entries listed.

Ideally the entries at each level do not overlap with each other; this can be quite challenging in practice. The goal is to reach the level when all issues or parts are clear to allow for a thorough review of potential impacts to a system which may be obscured at a higher level.

SCENARIOS

The scenario is one of the primary tools in futurism. Several possible future states of the world are predicted and perhaps fleshed out into narratives. These scenarios can be very useful in setting goals, as some possible future states will be preferable to others, plus they can be used to develop mitigation strategies to avoid adverse outcomes.

Scenarios provide a sort of road map to the future and give an insight into the dynamics of how the future might unfold. This type of information can be useful when planning for multiple contingent events and enable more robust decision making. A set of scenarios will be more qualitative than quantitative, which can pose an issue when presenting the results to senior management. They may be accustomed to dealing with a single best estimate; gaining support for the use of scenarios may prove challenging.

SYSTEM DYNAMICS

System dynamics differ from most modeling techniques in that the current state of a system has an impact on how it interacts with its environment. Many times one can assume that a system is closed to its environment without major consequences, but in the right situations a system dynamics approach can prove to be a superior methodology.

Figure 3 shows an example of population growth. A population is affected by both a birth rate and a death rate. If both were unchanging, you would expect to see either the population die off if the death rate exceeds the birth rate and to grow exponentially if the birth rate exceeds the death rate. When modeled as a dynamic system, a larger population experiences a higher death rate perhaps due to overcrowding, pollution or wars. The result is an S-shaped curve, where the population grows until the birth and death rates are about equal.

TREND IMPACT ANALYSIS

Trend impact analysis attempts to take surprise discontinuities in trends into account. A smooth curve is constructed along with a list of events that might have an impact on that trend along with their associated chances of occurring and the impact they are predicted to have on trend. The expected value of the trend impact is added to the smooth curve, resulting in an adjusted extrapolation.

For an example, assume a 5 percent baseline trend and an event estimated to have a 15 percent impact for two years and a 5 percent decrease thereafter. Also assume it has a 10 percent chance of occurring in each of the next three years. The expected value per year is calculated in Figure 4, which produces a slightly increased trend for four years followed by a decreasing trend.

Figure 3: Population Growth Model Where the Population Impacts the Death Rate

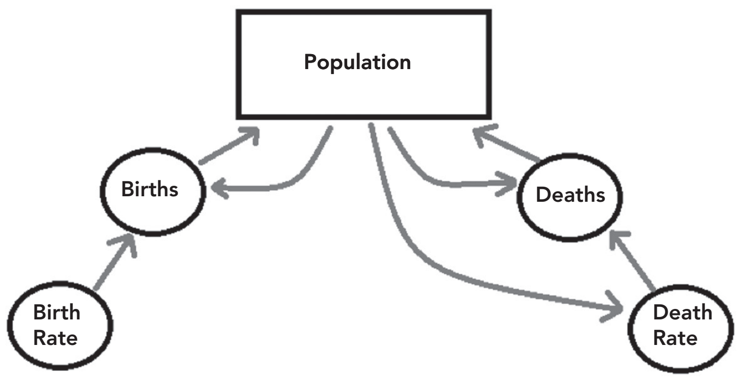


Figure 4: Derivation of the Example Event's Expected Impact on Trend

Impact Occurs in:	Year 1	Year 2	Year 3	Year 4	Year 5	Probability
Year 1	15%	15%	-5%	-5%	-5%	10%
Year 2	0%	15%	15%	-5%	-5%	10%
Year 3	0%	0%	15%	15%	-5%	10%
Expected Value:	2%	3%	3%	1%	-2%	

Figure 5: Baseline Growth Using 5% Trend

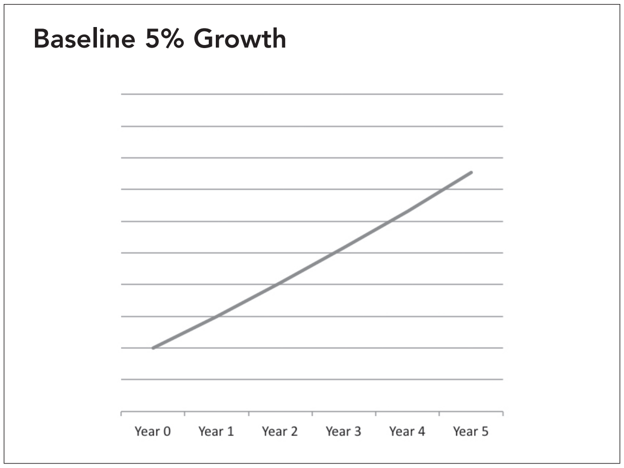


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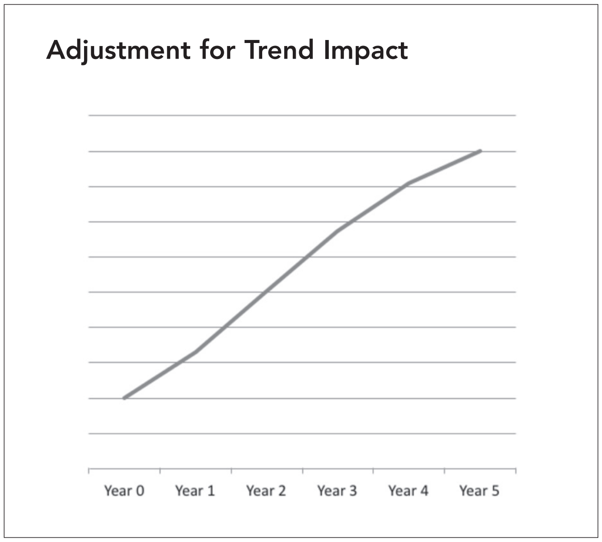
Figure 6: Growth Using Adjusted Trend



Trend impact analysis provides a range of possible trends rather than a single forecast. This can be an effective way to sensitivity test a critical rate for modeling purposes; however, the list of impacts evaluated will almost certainly be incomplete. Estimating the probabilities of events occurring and the value of their impacts can pose a challenge.

VISIONING

Visioning is the development of the goal of an organization, a preferred future that everyone is working toward. If everyone at an organization is invested in the vision, this can be a powerful motivational tool. However, when it is something generic like "provide excellent customer service," a vision can fall flat.

A good vision can be difficult to devise; ideally, it should be unique to an organization. Visions can be particularly useful during organizational changes to define a concrete goal and aid in maintaining employee morale.

USING FUTURISM AT WORK

Critical to adopting any of these techniques in the workplace is obtaining buy-in from organizational management and other key stakeholders. Several of these people are likely to be nontechnical staff, so being mindful of the audience is crucial to shaping one's communication appropriately. For example, when attempting to use a Delphi study it may be constructive to describe it as a type of survey, which will likely be more readily understood at first.

Developing a level of expertise and comfort with these techniques is very important to successfully implementing any of them. Hopefully, my brief overview has inspired a desire for further readings on one or more of the futurism techniques; a more detailed overview can be found in the Applied Futurism Study Note referenced at the end of the article. ▼

REFERENCE:

"Applied Futurism: An Introduction for Actuaries," by Alan Mills, FSA, and Peter Bishop, Ph.D. *http://www.soa.org/files/sections/applied_futurism.pdf*

Artificial Society Modeling with Sugarscape

By Ben Wolzenski

What is an artificial society model and how can it be useful? It's best to first take a step back and consider the broader subject of complexity science.[1] Actuarial science is applied to a real world in which events emerge due to the interaction of demographic, economic, technological, political and many other influences. The phenomena that result from such complex interactions are the subject of complexity science, and in particular agent-models, of which artificial societies are a sophisticated type. Artificial societies or virtual worlds are agent-based models in which the modeler determines the rules for agents and the environment. Just to be clear, artificial societies are not games in which the user has an "avatar" that interacts with the environment and possibly other avatars. In artificial societies, the modeler defines the rules for the agents and the environment and runs the model, but does not interact through an avatar.

One artificial society model that is useful to consider is called Sugarscape, which was invented and described by Joshua M. Epstein and Robert Axtell in their book, *Growing Artificial Societies*.[2] Think of this world as a two-dimensional space with cells. In the simplest version there are two piles of sugar and agents randomly distributed around the grid. Sugar grows in this world, but not evenly—hence the initial piles of sugar and barren spaces outside the piles. Initially, each agent starts with randomly determined genetic attributes (vision and metabolism), a random initial endowment of sugar, and a random maximum age within a defined range. Agents need to eat sugar to stay alive, and move about within their limited range of vision to find, accumulate and consume sugar. If at any time interval an agent does not have as much sugar as required by its metabolism, it dies.

The book starts with this simplest version, and then describes one additional feature at a time. There are simple rules for seasons (summer and winter), pollution, gender, 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. One example of the complex phenomena is that the long-term distribution of wealth (sugar) is highly skewed under a wide range of agent and environmental specifications, despite the fact that dying agents are replaced by new agents at random locations with random initial endowments of sugar.

The success of the book has led to the existence of an online applet, or demonstration program, which can be found at *http://sugarscape.sourceforge.net.*[3] This website contains documentation and a link to download and compile the source code as well as the demonstration applet.[4] The program is not exactly the Sugarscape model defined by Epstein and Axtell, but it has about the same level of sophistication. In this online model, sugar and spice are randomly

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distributed around the grid. The user-modeler determines a number of environmental factors, notably the size of the environmental grid; the probability that sugar or spice will grow in each cell as well as the rate of that growth; how much pollution is created and how quickly it is dispersed; the length of the seasons and how much growth varies seasonally. The user-modeler also sets many parameters related to agents—called citizens in the applet. These include the range of several parameters within which each citizen's parameter value is randomly determined. Key examples are the range for each citizen's age at death (provided he or she does not starve first); the age ranges for children, adults and seniors (who behave differently); and the ranges of vision and metabolism. Other model-specified parameters include the number and definition of cultural groups; the willingness of citizens to barter (sugar for spice or vice-versa) under different circumstances; the prevalence of diseases and immunities; the conditions under which citizens find mates and have children; and rules for the initial endowment of goods (sugar and spice) for newborn children. All told, there are over 50 parameters for which the modeler must either set values or accept the default values embedded in the online code.

How might we make practical use of such a model? It requires an interpretative adaptation. Let's consider the environment (grid) to be an area containing citizens who engage in economic activities with sugar and spice as financial resources. Summer and winter represent economic cycles, and pollution represents economic inefficiency or friction. We can set a realistic life span for citizens, with each time cycle of the model representing one year. For each citizen, we will keep track of the number of the citizen's children, diseases and immunities; the citizen's accumulated wealth and cultural group membership.

SUMMER AND WINTER REPRESENT ECONOMIC CYCLES, AND POLLUTION REPRESENTS ECONOMIC INEFFICIENCY OR FRICTION.

As a final step to make this relevant to a business in which actuaries are involved, we define the probability that any financial transaction is the specific one that we care about—let us use the purchase of an individual life insurance policy as an example. We could then define that probability as being influenced by numerous parameters, such as the citizen's age, wealth, cultural group, number of children (if any), and number of diseases and immunities. Furthermore, we could establish a probability that any citizen (and "trader" citizen with whom the citizen engages in a financial transaction) is a life insurance agent. The probability that any transaction is a life insurance purchase could then be influenced by whether the citizen and/or trader are life insurance agents.

In fact, I made modifications to the online model to do what is described above, and refined the model parameters and probabilities until I had a model in which 1) the population was relatively stable over a long period of time; and 2) the probability that a citizen would buy an individual life insurance policy in any year was close to that recently experienced in the U.S. resident population (about 3.4 percent). That enabled me to test the effect of changes in parameters on the population, on the frequency of purchases of individual life insurance, and in the variability of purchase frequency over numerous model simulations.

What would happen if I simulated an increase in unemployment by increasing the probability that any cell would not produce goods? What if delayed household formation were simulated by increasing the minimum age at which a citizen could have children? What if increasing productivity was simulated by increasing the maximum amount of goods that a cell could produce per year? What would happen if changes in estate tax laws were simulated by varying inheritance rules? Some of the model results were what we would expect in the real world (greater unemployment led to fewer purchases); other results were not intuitive but were food for thought (later household formation led to long-term greater purchases due to greater wealth accumulation); and some results were simply unforeseen by me (combining increased unemployment, deferred household formation and increased productivity sharply increased the variability of the number of purchases over multiple model runs).[5]

How practical is it to make use of such an artificial society model? I can only speak to my own experience. The time required to read *Growing Artificial Societies*; to learn enough Java to modify the online program (with no prior knowledge of object-oriented programming); to make and test modifications to produce the result described above; and to create a presentation of these results for the 2012 Life & Annuity Symposium totaled only about 75 hours. And now I can do further modeling with only incremental effort. Interested? I'd be happy to help you get started!

END NOTES

1 *Complexity Science—An Introduction (and Invitation) for Actuaries*, by Alan Mills, FSA, ND, is the landmark paper for actuaries about complexity science, and was published by the SOA two years ago. It is available at *http://www.soa.org/research/research-projects/health/research-complexity-science.aspx.*

2 *Growing Artificial Societies—Social Science from the Bottom Up* (1996), by Joshua M. Epstein and Robert Axtell.

3 Sugarscape Version 2.44.1 LL, by Abraham Kannankeril, is released under the GNU General Public License.

4 Additional instructions for downloading, compiling, customizing and running the program, with notes for different versions of Windows, are available from the author of this article upon request.

5 Detailed results are available from the author of this article upon request.

Predictive Modeling, A Life underwriter's Primer

By Mark S. Dion

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Use of predictive models is becoming more common throughout the business landscape. Underwriters need to understand the basic concepts as these models impact pricing, marketing and underwriting of life insurance products. This primer introduces and describes predictive modeling, the development of predictive models, types of models, advantages and disadvantages of such models, and closes with a glossary of terms commonly encountered when discussing models with other professionals in your organization. The article also addresses the distinction between predictive modeling and lifestyle-based analytics.

This primer does not explore the statistical modeling mathematics in detail. Nor does it represent an endorsement for, or an argument against, any implementation or use of predictive modeling.

PREDICTIVE MODELING: INTRODUCTION AND DESCRIPTION

Life insurance companies collect enormous amounts of data on clients and prospects. Since the inception of computer-based data gathering techniques, businesses have pursued methods to put the collected data to work to bring in more profitable business. Data mining, the process of culling and collating the huge volumes of collected transactions, laid the groundwork for bringing statistical analysis to bear on that vast repository. Predictive modeling, drawn from the realm of inferential statistical analysis, has been used for many years as a way to better understand and use the collected data to become more efficient, and hopefully, more profitable (Table 1).

Mark S. Dion

Simply stated, predictive models are analytical tools to predict the probability of an outcome or future behavior. These models build from a number of variables (factors) that are likely to influence future results or behaviors. Use of the term in this article is an extension of predictive analytics, in the context of data mining concerned with forecasting trends and probabilities. Additionally, predictive modeling sometimes uses non-parametric statistical analysis as a form of predictive inference, i.e., the models do not involve the estimation of parameters before the analysis is completed. Rather, these predictive models build from previously observed phenomena or observed outcomes. Analysts often use Bayesian methodology (q.v.) to build predictive models.

In predictive modeling, data is collected for the relevant predictors, the data is cleaned, a statistical model is formulated, predictions are made and the model is validated (or revised) as additional data becomes available. Models may employ simple linear equations, decision trees or complex neural networks. Most are built using sophisticated mathematical modeling software. During the development of a model there are usually many models and factors reviewed. The goal is to find the optimal uplift, known as "lift," to the hoped-for outcome. Lift could be described as the model's effectiveness, its ability to predict outcomes. Those outcomes might include reduced costs of acquisition, higher direct marketing response rates, more cross-selling opportunities or greater numbers of returning customers.

TABLE 1
Use of Predictive Models

- Capacity planning for scarce resources
- Change management
- City planning
- Customer relationship management (CRM)
- Disaster recovery
- Engineering
- Fraud protection—Automotive insurance claim fraud
- Geology and oil exploration
- Health insurance utilization and renewals
- Marketing—Credit card campaigns, Amazon, Netflix and iTunes recommendations, uplift **Marketing**
- Medical diagnosis and testing
- Meteorology
- Security—Spam filtering
- Security management

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Models generally add weight to more-recent behaviors and actions. Predictive models should not be allowed to stagnate because conditions and factors upon which a model is built can change over a period of time. Well-constructed models can increase efficiency and decrease costs; poorly constructed models may increase risks to a company's bottom line.

A Simple Example

A customer's gender, age and purchase history might predict the likelihood of a future sale. If the purchaser's history included details about genre, characters or author of book, or movie purchases, the model may allow specific types of offerings to their clients—e.g., iTunes, Netflix and Amazon recommendations—the model's lift providing for increased sales. Offer the client items similar to those purchased previously, although the similarities might not be obvious without a model. When purchasing movies, was it the genre, star, co-star, director or plot that captured the purchaser's interest? Would the purchaser be interested in items similar to those purchased by people who purchased the same item? A well-constructed model looks at all of those factors and more, to provide recommendations that optimize profitability and increase sales.

Life Insurance Example

After data analysis by a life insurance company, a model is applied to incoming applicants that looks at age, gender, admitted tobacco use, face amount, admitted family history, negative admitted personal medical history, current lipid findings, current hemoglobin $A1_C$, current GGTP, BMI, cotinine results and a pharmacy record check. The model score provides insight as to which applicants require an APS ordered as an automatic requirement and which do not. A well-constructed model would provide a targeted population significantly smaller than a simple age-amount requirement grid. The resulting cost savings may be applied to the wider use of underwriting requirement sentinels that provide a better cost benefit ratio.

Do not confuse predictive modeling with lifestyle analytics (LSA) also known as lifestyle-based analytics (LBA). Predictive models may be built using a multitude of factors and data sets, including aggregate results of the many underwriting requirements that underwriters have been using for decades. The example described above uses familiar underwriting tools. In addition, it is not out of the question when a model uses various LSA factors: geographic regions, gym memberships, customer purchase histories, magazine subscriptions, daily travel distance, etc. LSA combined with predictive modeling might be used in straight-through processing environments. The implications of such models are beyond the scope of this introduction.

TABLE 2

Life Insurance Predictive Models

- Agency evaluation
- Claims review
- Marketing—Customer segmentation, cross-selling, price optimization
- Pricing
- Reserving
- Risk selection scoring

Risk Selection Applications

- Determining the advisability for ordering Attending Physician Statements or other requirements
- Fraud investigation triggers and over-insurance identifiers
- Preferred screening tools
- Risk scoring for final decisions

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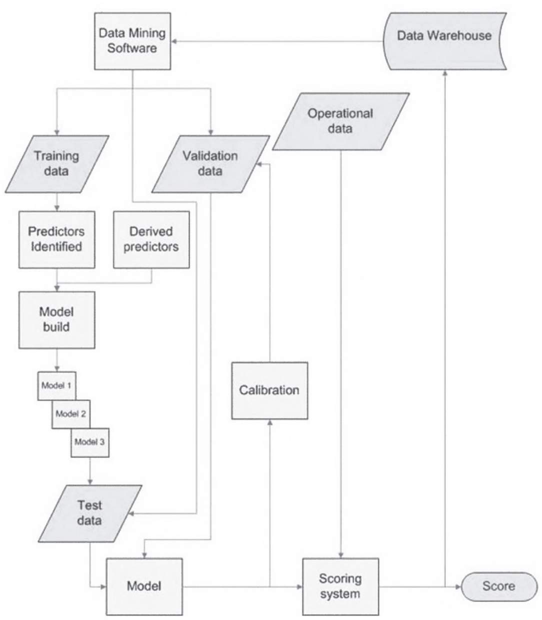
DEVELOPING A PREDICTIVE MODEL

Your company may well be using predictive models in various ways. Predictive modeling is used by various insurers to identify auto or health claim fraud, utilization reviews, marketing approaches, direct response mailings, etc. Incurred but not reported claims (IBNR) calculations, done for financial reporting purposes, might involve a form of predictive modeling. Application of predictive modeling techniques for life insurance underwriting is not widely in use currently, but interest is growing. The Society of Actuaries has sponsored symposia and presentations, and the number of published articles on the topic is growing. In the future, predictive models may become common practice in our industry. The following describes only the barest outline of the work involved with development of a useful model. See Figure 1.

Figure 1: Predictive Model Build Process



Models Begin with Data Mining

The goal of data mining is to find patterns in data. Data, once separated from the statistical noise, may unveil patterns of behavior leading to efficient and profitable business.

1. Data and Algorithm Preparation
   a. Collect data for predictive variables
   b. Clean the data
   c. Assign data distribution to three portions: training, test, validation
      i. Data should be drawn from the same source, at the same time, properly randomized and divided, to be used through the stages of model development

Establish the logic and algorithm

2. Develop decision trees
3. Use training data to identify factors and predictors *Model builds require some trial and error to get the most lift.*
4. Build the model
   a. Build multiple models attempting to optimize lift
   b. Test the models using a portion of the identified data
   c. Watch for discordancy
   d. Calibrate
5. Validation

Implementation and maintaining a good model

6. Implementation and use
7. Scoring system established
8. Establish audit procedures and feedback to data warehouse
9. Calibration
10. Once a model moves to a production environment, the results require regular monitoring and recalibration.

MODELS IN PRODUCTION

When the model has proven itself and provides sufficient lift, a scoring system will provide guidance. For example, a scoring system might provide a score designed by the model development team to suggest whether to order an APS. Based on the factors used in the model, a score of 0-60 might yield a pass result with no further action. A score of 61-74 might generate a "refer to underwriter" with a recommendation for an APS. The next class of 75-95 might generate an automatic APS. Finally, a score of 96-100 might raise a red flag to the underwriter that, based on this sample model, there may be significant anti-selection or perhaps a suspicion of attempted fraud.

Aside from the score, the system should feedback to the data warehouse providing additional data elements and outcome results that can assist in further improvement of the model.

TYPES OF PREDICTIVE MODELS

The following list provides a glimpse into the number of model possibilities. Unfortunately, fuller descriptions exceed this article's intent. The reader should consult the references for additional description and examples.

1. Classification and Regression Trees (CART)—Sort groups and population into smaller discrete branches and nodes.
2. Cox Proportional Hazard—A form of survival modeling and a hazard function. Hazard functions are an estimate of the relative risk of a terminal event, such as a death. This survival model is a multivariate technique for analyzing the effect of two or more metric and/or non-metric variables on survival.
3. Decision Tree Analysis—Sorts decisions into smaller branches and nodes, weighting the decisions based on factors identified.
4. Generalized Linear Model (GLM)—Linear or logistic regression models. The most commonly described in life insurance literature, relatively speaking, this is a simple way to model using multiple variables that interact in ways that are not obvious using univariate analysis. See expanded discussion below.
5. k-Nearest Neighbor (kNN)—Uses data that aggregates based on classification. Predictions are based on population density of the factors in the training sample. A simple system often applied to "machine learning."
6. Logistic Regression—Logistic regression is a category of statistical models referred to as generalized linear models (q.v.). The goal of logistic regression is to predict the category of outcome for individual cases using the most efficient model.
7. Naïve Bayes Classifier—Assumes that the presence (or absence) of a particular feature of a class is unrelated to the presence (or absence) of any other feature.
8. Neural Networks (NN)—As the name suggests, models that have the structural appearance of animal neurons. The concept suggests that many inputs can result in a single (or at least smaller number) output. NNs can produce multiple outcomes however. (Figure 2)
9. Regression Splines—Implies regression analysis that requires data points that must be interpolated, or somehow smoothed.

While this article has not to this point dwelt on the statistical details of predictive modeling, an example chosen from above will expand the description of one of the model types encountered in the actuarial literature.

Generalized Linear Modeling (GLM)—Extends linear regression models to both non-normal distributions and linear transformation (transformation of linearity). First we can describe a conventional linear model that specifies the relationship between a dependent variable Y, and a set of predictor variables, the X's, so that

$$Y = b_0 + b_1 X_1 + b_2 X_2 + \dots + b_k X_k$$

In this equation, b_0 is the regression coefficient for the intercept and the b_i values are the regression coefficients (for variables 1 through k) computed from the data. Linear models as described make a set of somewhat restrictive assumptions:

- Dependent variable y is in normal distribution and conditioned on the value of predictors

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- A constant variance, regardless of the predicted response

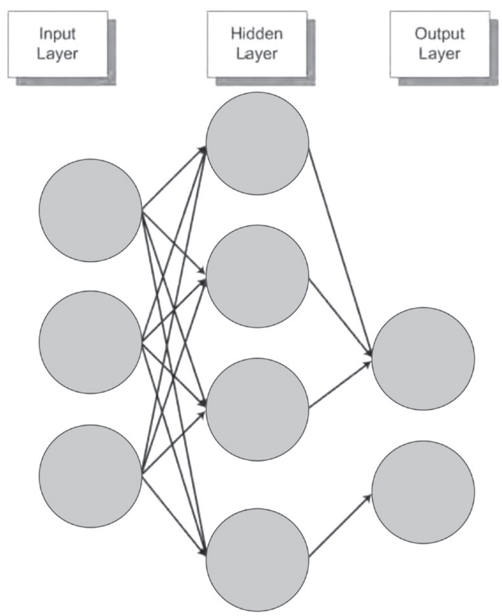
The advantages of linear models with the above restrictions are:

- An easy-to-interpret model form
- Relatively simple computations
- Readily analyzed to determine the quality of the fit

Generalized linear models relax these restrictions. They adjust responses that violate the linear model assumptions in two ways:

1. Link functions model responses when a dependent variable is assumed to be related to the predictors in a non-linear fashion. These functions, and there are many, transform a target range so the simple form of linear models can be maintained.
2. Variance functions used, which express the variance as a function of the predicted response. This allows responses with variances that are not constant.

Figure 2: A Simple Neutral Net (NN)



ADVANTAGES OF PREDICTIVE MODELS

1. Ability to detect complex non-linear relationships between dependent and independent variables.
2. Ability to detect all possible interactions between predictor variables.
3. Availability of multiple training algorithms.
4. Some forms of predictive modeling, neural nets for example, require less formal statistical training.
5. Bayesian methods can arguably be used to discriminate between conflicting hypotheses: hypotheses with very high support should be accepted as true, and those with very low support should be rejected as false.

DISADVANTAGES OF PREDICTIVE MODELS

1. A perceived "black box" nature, making it difficult to describe and explain results; the proprietary nature and structure of each model reinforces the perception.
2. Subject to bias, some may argue that inference methodology might be biased by perceptions held before any evidence is collected.
3. Computational intensity requiring adequate technology infrastructure and statistical analysis acumen.
4. Prone to overfitting and therefore inaccuracies caused by fluctuations in irrelevant or erroneous predictors.
5. Sensitive to changes in conditions and therefore require close monitoring of the environment to which the model is being applied.
6. Models as mathematical constructs can at times yield results that fly in the face of common sense.
7. Regulatory concerns if models are not adequately understood or explained.

MODELING CONCEPTS AND TERMS

The following terms and concepts provide readers new to the area of predictive modeling a basic lexicon, useful for discussions within their respective organizations.

Algorithms—Expression of a problem as a sequence of logical steps.

Bayesian Methods—Based on Bayes' theorem. Bayesian inference presumes collection of evidence that is either consistent with or inconsistent with a given hypothesis (H1). As we gather evidence, our confidence in the hypothesis ought to change. Given sufficient evidence, the degree of confidence should become either much higher or much lower. Underwriters should already be familiar with other Bayesian models, specifically the specificity and sensitivity of a test, and the test's corresponding positive or negative predictive values.

Calibration—During development and thereafter, as the environment changes, or to maintain lift, predictive models must be calibrated, reworking predictors and factors. Some circumstances will change frequently, for example, a new life insurance marketing plan, a new product with different pricingand expense assumptions, or outside influences such as competition with similar products.

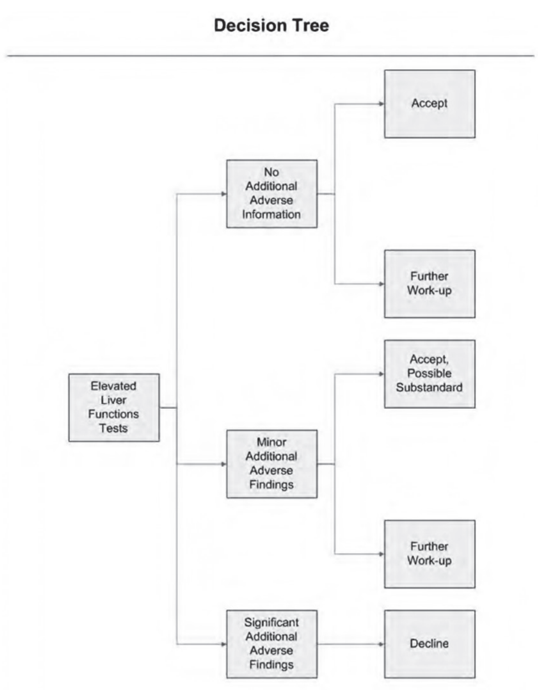
Data Mining—Data mining is the process of finding patterns and correlations among dozens of data elements in relational databases, especially large databases. This process allows a user the ability to analyze data from different perspectives and summarize the data into useful information. The software to mine the data is often a different tool than one used to build a predictive model.

Decision Trees—A decision tree as discussed here depicts rules for dividing data into groups. The first rule splits the entire data set into a number of pieces, and then another rule may be applied to a piece, different rules to different pieces, forming a second generation of pieces. In general, a piece may be either split or left alone to form a final group. (Figure 3)

Derived Predictors—Mathematically transformed predictor variables, sometimes known as synthetic predictors. These predictors are derived from mined data and through application of algorithms developed during the model-building process. They were not identified as useful until discovered during the development phase.

LBA MAY BE CONSIDERED IN BUILDING PREDICTIVE MODELS FOR LIFE INSURANCE RISK SELECTION, BUT IT SHOULD NOT BE CONFUSED WITH THE TERM PREDICTIVE MODELING.

Figure 3: A Simple Neutral Net (NN)



Lifestyle Based Analytics—Most readers are familiar with the links between lifestyle characteristics and various medical conditions. Various data aggregators and vendors now offer over 2,000 pieces of information (data fields) on various applicants. While a powerful tool for marketing segmentation, which can arguably raise flags concerning higher incidence of disease based on the population predictors, LBA cannot provide the same predictive value to which we are currently accustomed from routine fully

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underwritten business on an individual case-by-case basis. LBA may be considered in building predictive models for life insurance risk selection, but it should not be confused with the term *predictive modeling*. Robust life insurance predictive models can be prepared without LBA.

Linear Regression—Regression uses the value of one variable in a pair of variables, to predict the value of the second variable. Linear regression attempts to pass a line through the observed variable pairs in a given sample data set. Models built using linear regression are fine when the value of one variable changes, is conditional, upon the value of the other variable. If we wish to study the probability distribution of both variables (or more variables) as they both change, we move to the realm of multivariate analysis (q.v.).

Logistic Regression—Logistic regression predicts the probability of occurrence of an event by fitting data to a logistic curve. Consider it a generalized linear model used for binomial regression. One example, the probability that a person has or will develop diabetes within a specified period might be predicted from knowledge of the person's age, sex and body mass index (BMI). Logistic regression is used extensively in medical literature.

Multivariate Analysis—A statistical technique that allows analysts to review several dependent variables simultaneously. Multivariate analysis helps summarize data and reduce the number of variables necessary to describe it. The multiple dimensions involved in data mining require statistical tools capable of measuring the effects of the interactions of many variables in action at the same time.

Neural Net—Named for the resemblance to an anatomical neural system, a non-linear data modeling tool, used to model complex relationships between inputs and outputs or to find patterns in data. The multiple inputs, once processed by the NN model, produce a single output, if things turn out as hoped.

Input is acted upon by factors not observed, called the hidden layer, to provide an output. The hidden layer allows the action based on recognized patterns. While the hidden layer can theoretically become quite large, the result can be overfitting (q.v.).

N.B. Predictive models may produce more than one output.

Overfitting—Overfitting exists when the model in fact describes noise, another expression for statistical random error, rather than the studied relationship. Overfitting will usually cause a model to perform poorly as small fluctuations in data can cause inaccurate results. Too many predictors included in a model make this problem more likely.

Parametric vs. Non-Parametric Statistical Analysis—When certain assumptions about the underlying population are questionable, non-parametric tests can be used in place of their parametric counterparts.

CLOSING

The literature relating to life insurance applications of predictive modeling techniques is relatively sparse compared with other disciplines. While the techniques do lend themselves to life insurance business, they are not as widely used as in auto or health insurance. Recently interest by actuaries and business heads suggests these tools will become much more common and be with us as a risk selection tool going forward.

The reader should refer to the Society of Actuaries website for additional information on this topic at *www.soa.org.* For additional information regarding data mining, refer to the excellent introduction by Berry & Linoff, 2004. ▼

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What Is Complexity Science?

By Glenda Maki

Perhaps you've heard the name, but aren't exactly sure what complexity science is. You've come to the right place! ***In this roundtable, six members of the SOA's*** Forecasting & Futurism Section ***talk about complexity science and how it can benefit actuaries. Visit*** *http://www.soa.org/forecasting-futurism/.*

Participants:
Alberto Abalo, principal, Oliver Wyman
Donald Krouse, VP & appointed actuary, Transamerica
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HOW LONG HAS COMPLEXITY SCIENCE BEEN AROUND? HAS IT BEEN REFERRED TO BY OTHER NAMES?

Wadsley: To be fair, complexity and the study of complexity have been around a LONG time. That said, complexity science as we think of it today is fairly new. The goals of creating artificial intelligence can be traced to the beginning of the computer age. While many of the subtopics of complexity science emerged at different times, one of the landmarks was the invention of the genetic algorithm by John Holland in the 1960s at the University of Michigan. Some earlier computer scientists in the 1950s actually studied the idea of evolutionary systems with the goal of using it as an optimization tool for engineering problems.

Ramsey: There were many researchers in various fields dancing around the edges of complexity science long before the current name and techniques were adopted. One might, for example, interpret the invisible hand of Adam Smith as an early non-mathematical example of an emergent behavior, and similarly for Friedrich Hayek's 1940s work on self-organization. Emergence of macro properties from simple micro-level rules and of self-organization without any external or central control, are properties of complex systems.

Glenda Maki was communications program coordinator with the Society of Actuaries at the time this article was written.

Snell: I believe the important thing for actuaries to know is that classic, deterministic means of solving problems have limitations in a world that has many interactions and no requirement to adhere to a theoretical model.

Abalo: I hate to begin my blogging career by referencing Wikipedia, but who can improve on this elegant chart? Visit *http://upload.wikimedia.org/wikipedia/commons/2/25/Complexity-map_Castellani.jpg.*

IS COMPLEXITY SCIENCE "SCIENCE?"

Krouse: There are many definitions of "science." From the perspective of a systematic approach to assembling knowledge and theorems that are testable and predictable, some aspects of complexity science may not neatly fit (after all, one of the objectives is to identify those areas that are not necessarily predictable). However, from the perspective of defining knowledge about natural systems, complexity science is certainly a science.

Abalo: I do not view "complexity science" as an individual field of study. Instead, I see it as a paradigm that touches on all areas of scientific inquiry, from mathematics and biology to economics and psychology—and, yes, even actuarial science. Where we typically study systems by breaking them into components, complexity makes us think of a system as we instinctually know it—greater and different from the sum of its parts. Ant colonies, locust swarms and human economies do not follow the rules we associate with the individuals that make up the system. In other words, we cannot define these systems in their entirety by defining how ants, locusts and humans act in isolation. Complexity differs from the current paradigm of scientific inquiry in that it employs inductive reasoning to investigate patterns of interaction and adaptation and concepts of emergence and self-organization in social systems.

Ramsey: Karl Popper taught that a theory is scientific only if it is "falsifiable," or in other words, if that theory is false then it must be possible to so demonstrate experimentally or through observation. A theory that could not be falsified is in this sense not scientific. Many aspects of complexity science appear to be falsifiable and therefore to be science. Complexity science is a broad term with somewhat ill-defined boundaries, so it is certainly possible that not all of complexity science qualifies as science under this perspective. Visit *http://plato.stanford.edu/entries/popper/.*

Wadsley: According to Melanie Mitchell in her book, *An Introduction to Genetic Algorithms,* "Science arises from the very human desire to understand and control the world." With the spirit of that definition of the motivation of science, complexity science fits into this nicely. Visit *http://web.cecs.pdx.edu/~mm/.*

WHAT ARE SOME OF THE KEY TOOLS/ TECHNIQUES ASSOCIATED WITH COMPLEXITY SCIENCE?

Snell: Inductive reasoning takes many forms: genetic algorithms, cellular automata, serious games, Delphi studies, etc.

Wadsley: Some tools are being used today in the financial world (genetic algorithms and predictive modeling). Some have potential but it's not been fully realized (network science, fractals, cellular automata and deterministic chaos). Others are heavily used, but are not considered by all to be included in complexity science (behavioral economics).

Wolzenski: I would cite (and strongly recommend) the landmark paper by Alan Mills, FSA, ND (©2010 Society of Actuaries): "Agent-based models are the heart of complexity science, and the four archetypal models are networks, cellular automata, artificial societies and serious games."

IS IT FAR-FETCHED TO IMAGINE A SYSTEM THAT OUTSMARTS THESE EXPERTS SO THAT THE ALGORITHM EVENTUALLY WRITES ITSELF?

Krouse: The Forecasting & Futurism Section has been busy compiling a list of resources and examples for each of these tools and techniques. These are available on the SOA website *(http://www.soa.org/professional-interests/futurism/fut-detail.aspx.)*

ONE CAN SEE HOW FRACTALS CAN BE USED TO MEASURE COASTLINES OR ESTIMATE CARBON EMISSIONS IN THE RAIN FOREST. WHAT ARE SOME OF THE APPLICATIONS?

Ramsey: The use of Mandelbrot's multifractal models in modeling financial markets seems to hold promise in risk management and needs to be further explored. It offers another approach to the fat-tail problem, in which outliers occur more often than most models predict, and the tails are of course a key focus of risk management.

Abalo: In life insurance, advanced algorithms are replacing blood testing and medical exams. Today, those algorithms are created (or at least vetted) by a team of insurance professionals: underwriters, actuaries and administrators. Is it far-fetched to imagine a system that outsmarts these experts so that the algorithm eventually writes itself? Health care providers are already beginning to embrace the benefits of machine-based learning. Visit *http://www-03.ibm.com/press/us/en/pressrelease/37235.wss.*

Wadsley: While there are several books that claim to use fractal for technical analysis, the real value may come

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from understanding other hard-to-measure "borders" such as value at risk (VaR) and conditional tail expectations (CTEs). Dynamical systems focus on the gross behavior of all solutions instead of analytically precise local behavior, which can be valuable in understanding tail risk.

Snell: Our DNA is folded into a fractal so that a 1.8 meter strand can fit neatly into 1/100th of a millimeter. Our lungs are fractals to maximize surface area for the given volume. Amazon.com sells many books on fractal analysis of the stock market. We may discover that a virus spreads in a fractal manner or that a beneficial bacterium may exhibit fractal tendencies. Perhaps a fractal is a more effective delivery mechanism for medicines.

Krouse: More generally we often find that actuaries are expected to be able to completely and accurately "predict" the future. Without a crystal ball, this is unrealistic. However, using some of the tools of complexity science, an actuary can define a set of conditions, assign probabilities, etc., and from these derive a likely outcome or range of outcomes.

As a simple example, we need look no further than the current low interest rate environment. By many "probabilistic" measures, current interest rates are highly unlikely—and yet they exist today. In hindsight, could some complexity science tools have identified these scenarios? Absolutely! Would people have reacted to them? Well, hindsight's always 20/20. Visit *http://blog.soa.org/2012/03/12/the-low-interest-rate-environment-a-roundtable-discussion-with-members-of-the-soas-smaller-insurance-company-section-part-1/.*

HAVE TRADITIONAL EMPLOYERS OF ACTUARIES BEEN RECEPTIVE TO COMPLEXITY SCIENCE APPROACHES TO PROBLEMS? WHY/WHY NOT?

Snell: Property and casualty insurance companies are embracing complexity science techniques (especially predictive modeling) at a far more rapid rate than life insurance companies. Health insurance companies are now utilizing serious games to test therapies faster than possible (or allowable) with human patients.

Abalo: Why not ask if we, as insurance professionals, can cut through organizational red tape to convincingly demonstrate to our employers that novel approaches merit an investment in resources? The powers that be would likely be very receptive to approaches that improve the efficiency and accuracy of tools and processes we already use and potentially create competitive advantages by opening new areas of inquiry. I believe complexity science offers sufficient benefits to overcome the human tendency to simply do what has worked in the past.

Ramsey: Much of the work of actuaries involves projecting future cash flows and discounting them back—the details may differ from pricing an insurance product to setting a U.S. GAAP reserve to valuing a pension plan; but nonetheless, the idea that fundamentally we are projecting cash flows and discounting them back holds.

Traditional employers of actuaries will be receptive to complexity science approaches to problems when those approaches offer better ways to project cash flows and discount them back.

To date, I do not believe that actuaries have done much exploring of ways that complexity science techniques can improve our projections, but as the number of actuaries with an interest in, and familiarity with, complexity science increases, I believe that this will happen.

Krouse: I think the response has been varied. As with anything "new," it does take time to become accepted. Having said that, we must also be cautious that complexity science tools are not viewed as a panacea. Like any actuarial or financial tool, there are certain applications where they are of best use.

Wadsley: As the field continues to be refined, I feel it will be increasingly used. "I expect that the children of 50 years from now will learn cellular automata before they learn algebra."—Stephen Wolfram, 2006. *Visit http://www.stephenwolfram.com/.*

IT LOOKS LIKE THE FORECASTING & FUTURISM SECTION FIRST GOT INVOLVED WITH COMPLEXITY SCIENCE IN 2010, AND THERE HAVE BEEN SOME WELL-ATTENDED/HIGHLY RATED SESSIONS AT SOA MAJOR MEETINGS. WHAT'S NEXT IN YOUR PLANS? OR WHAT WOULD YOU LIKE TO SEE?

Krouse: We certainly have had some well-attended sessions in the past couple of years. We anticipate sponsoring our section's first webcast later this year. Our longer-range objective is to raise awareness of the tools and techniques available. We plan to accomplish this initially through meeting sessions, webcasts and our section newsletter, but we are also working on including more complexity science topics in the SOA exam syllabus. Membership in the Forecasting & Futurism Section has grown significantly in the past two years. Obviously, actuaries are interested in these topics, and I encourage all members to become involved with the work that we are doing. *Visit http://www.soa.org/forecasting-futurism/.*

Ramsey: In addition to sessions at SOA meetings and webcasts, we will also continue to co-sponsor sessions and research, not just in complexity science but in other fields of interest to us as well, such as nontraditional forecasting techniques, demographics and futurism.

I would like to see a wider variety of tools for practicing actuaries to select from in order to better perform our roles. Some of these tools may come from complexity science approaches, but whether they arise from complexity science or elsewhere is less important than continuing to improve and expand our capabilities.

Snell: Genetic algorithms will become far more popular among actuaries in the coming year, as will serious games, cellular automata and behavioral science.

Wolzenski: Artificial society models can be used for sensitivity testing and forecasting. A background article on artificial society models was in the summer 2012 newsletter of the Forecasting & Futurism Section, and a further article will be in the winter 2012 newsletter.

Wadsley: Through my study of complexity science (genetic algorithms in particular), it appears that other professions have been much more successful at using these new techniques. I'd like to see us continue to use the lessons learned from those other professions to make our own successes and growth in the field.

Abalo: I understand our day jobs often demand 150 percent of our focus. With exams long behind us, it can be challenging to find time to explore new approaches, however interesting. Further, moving beyond satisfying personal interests and actually demonstrating use to an employer

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may seem impossible, if not laughable. I want actuaries interested in complexity to be able to avoid “starting from scratch” and turn to our section as a resource for continuing education and examples of how they can successfully implement these concepts in our corner of the universe. Examples like Ben Wadsley’s use of genetic algorithms in portfolio optimization and Ben Wolzenski’s explorations of how artificial societies can be used for forecasting insurance needs demonstrate that actuaries can—and should—use the tools emerging from complexity science. Stephen Hawking has said the 21st century will be the century of complexity. Let’s not miss out! ▼

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