SOCIETY OF ACTUARIES
PREDICTIVE ANALYTICS AND FUTURISM SECTION

PREDICTIVE ANALYTICS AND FUTURISM
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Impact of Exponential Technologies on Actuarial Profession

By Syed Danish Ali

This article's aim is not to elaborate on a specific technology case, but to argue the case for exponential technologies as a category while emphasizing that it's the convergence between them that also matters significantly when assessing their impact on actuarial practice in the upcoming future.

Exponential technologies can very easily impact the actuarial profession's practice in both good and bad ways. What ultimately will determine the outcome is how actuaries react to these changes and their willingness to update their mindset, skillset, and understanding of new emerging risks, new business models made viable by tech and the broader context meta trends.

The exponential technologies are generally classified as being minute in the beginning. However, it rapidly builds upon itself to reach such high levels that could not be anticipated if we had followed its journey linearly. Another way to look at these technologies is that they cause a paradigm shift in the way business-as-usual is conducted and that they act as a foundation over which countless other innovations are made. For instance, the internet was the foundation that made Google, Facebook, Amazon, etc., a reality. Countless apps from unicorns like Uber to other apps were made upon the android revolution that allowed people to make such apps. Therefore, it's not difficult to see how exponential technologies could enable ecosystems, marketplaces and collective platforms that now appear minute and distant, but can quickly become the new normal.

The convergence of these technologies matter because in problem solving, the problem is attacked from a number of perspectives and tools to create a solution that fulfills the needs of various stakeholders and solves the puzzle piece by piece. It is then that we see ground level impact and progress. Given these technology options, it is worthwhile thinking about how these ideas would fit into the larger context, sitting alongside the sharing economy, the Internet of Things, machine learning and smart cities. Most likely, the tech convergence will mean multiple options of travel running parallel to each other at the same time.

FUTURISTIC APPLICATIONS

Unfortunately, there has been little cross-pollination between actuaries and futurists even though most of them inquire about the same complex domains and have much to learn from collaboration. These exponential technologies fascinate us everywhere as humans and as actuaries as well as ignite our innate curiosity and quest for exploration and overcoming our limitations.

Now that we have built a basic mind-map of core building blocks from the previous section, we can build a narrative that is more interesting than simple explanations through examples. Imagine some real-life scenarios (some are real, and some are yet to materialize):

1. Quantum computers increase the power of our tools exponentially and we can discover and execute with far more speed and depth than ever before possible.

2. Blockchain with IoT and AI renders insurance invisible to the customer.

3. Augmented reality helps in creating new virtual worlds and avatars[1] that require insurance protection.

4. Your car senses your travel and automatically buys insurance on an on-demand basis by the mile. A machine buys its own liability insurance automatically with cryptocurrency like IOTA.

5. Wearable exoskeletons give law enforcement and factory workers superhuman strength and agility and reduce the workforce's claim frequency for accidents. But when an accident occurs (through hacking or otherwise), the severity becomes more uncertain.

6. Brain-computer interfaces (BCIs) merging with our brains to create super-human intelligence (for example, Neural Lace of Elon Musk)

7. Digestable smart pills, and health wearables that directly assess our mortality and morbidity risks.

8. You can get life insurance from taking a selfie. The selfies are analyzed by an algorithm that medically determines your biological age through these images (already being done by Chronos software of startup Lapetus[2]).

9. Your fridge understands your regular shopping and stocking habits and finds that an item like milk is getting old, so it buys milk through online shopping. Your fridge will be continuously restocked based on your most common habits. For something new or unusual, you can continue to independently buy your items.

10. Longevity research helps in prolonging healthy human lifespan disrupting the life insurance, pensions, and savings industries as well as social order itself in ways not yet imagined.

11. Lloyds insurance marketplace faces tough competition from SingularityNET, where many people go to exchange risk transfer of the future. SingularityNET is a decentralized, full stack AI marketplace platform with machine learning and blockchain enabled in opensource for anyone to create ecosystems and transact on them just like any other marketplace.[3]

12. Self-driving cars interact with each other on the smart grid to avoid accidents or collisions by forming a "collective hive" state of mind.

13. Sensors detect an upcoming burst in a pipe and send a repairman to your home before the pipe bursts. An insurer has offered a sharing plan for the customers to install these IoTs affordably.

14. Your chatbot is your personal assistant. It shops for you, its offers emotional support when you are depressed, senses when you need to buy insurance for traveling, etc., handles your daily chores and keeps you updated on your daily schedule that you have made in collaboration with the bot. The bot alerts you that you haven't studied for the actuarial exam as you had scheduled!

15. You have a 3D printer for making new toothbrushes. The current smart toothbrush senses that its filaments are about to get worn out, so it sends a signal to the 3D printer to make new filaments. 3D printers are used to make just about everything from our current tools to new materials, superstructures and tools that we haven't yet perceived.[4]

16. Instead of bee swarms, we now see drone swarms flying off carrying out their tasks in collective swarm intelligence.

17. Climate change, environmental focus, poverty alleviation and micro-finance and impact investment has become a major source of attention for actuaries to better their planet and its inhabitants.

18. Actuaries have become Mars and moons citizens and are applying analytics on how that environment changes the normal exposures of insurance.

19. Massive simulations are done now instead of spreadsheet models. The Apollo Baidu system of simulations for autonomous vehicles, machine teaching, reinforcement learning, and complexity science is being applied. Who knows, we might even dabble in trying to make "general AI" algorithms like the Machine Intelligence Society does.

20. How is it possible to accomplish all these things? It will be possible as data janitorial work, which used to take majority of an actuary's time, is automated and silos are broken down. Actuaries stand on the giant shoulders of AI with blockchain and automated machine learning, leaving them free time to achieve their true potential.

There are countless real-life scenarios like these, limited only by our imagination.

The scenarios pictured above will seem far off and distant to many, especially as current realities of insurers are still the same as they were 200 years ago. The Fourth Industrial Revolution is still nascent and emerging, but exponential results can mean that it becomes a large part of our lives very soon. We have yet to see the full-blown utilization of exponential technologies, but we are certainly in the stages of seeing its dawn and emergence.

It's then a simple notion at heart: as society does something new, the need for insurance remains and the exposures change. For Martian insurance to become a reality we first must reach Mars; for 3D printed body organs these must become reality for insurers to assess the change in mortality due to this. Change will be so radical and emerging exponentially, that the actuary must become an applied futurist to be able to assess these changes in exposures and forecast what new and emerging risks and opportunities will soon arise.

Like Jeff Bezos, we ask ourselves "when everything changes, what doesn't change?" There will always be risk; there will always be insurable items and need for insurance. There will always be a need for analytics and data-driven decision making. Countless emerging risks will become a more important aspect of our daily lives and multi-disciplinary teams based on cross specialization will be needed, as well as strategic thinking skills.

The real test will be how actuaries respond to the emerging risks brought about by exponential technologies. Emerging risks and futurism have to be given serious time and attention by actuaries to forecast not just numbers now, but emerging risks and opportunities. Hyperloop, blockchain applications, crypto currencies in investment, space hotels' insurance, making swarm algorithms for drones and all others should be evaluated using erudite training. Whether its blockchain or drones or new emerging products, risks and opportunities, actuaries can keenly evaluate their risks and suggest preventive mechanisms to address them. They shouldn't have to wait any longer for years of credible data to emerge to start pricing because they know that changes happen too fast now.

If we think that we have conquered nature due to all of these innovations and solved all our problems, then we would be sadly mistaken. Reality is highly complex, has higher order nonlinear effects and the world is VUCA; volatile, uncertain, complex, ambiguous. Some instances are:

1. Full self-driving autonomy is an incredibly difficult task because every foreseeable topological data of the environment has to be mapped in instantly whether its night or day, winter or summer, rural or urban, developed or developing, etc.

2. The human brain is arguably the most complex unit in the universe and trying to augment that through BCIs has almost unfathomable engineering challenges.[5]

3. Space has extremely hostile conditions and again engineering nightmares are commonly encountered by the people trying to make us humans a space faring species. Also, as astrophysicists and theoretical physicists will testify, we have hardly scratched the surface of understanding the cosmos of which we are a part of. We don't even have a "theory of everything" yet that combines general relativity of the macro structure to the quantum mechanics of the infinitesimally small micro-structure.

4. Genetic engineering, longevity research, geo-engineering building quantum computers, nuclear fusion all have to contend with similar confounding perplexities.

5. We have to face human-made challenges like climate change, wars, poverty, our collective irrationalities, etc.

6. Unintended consequences of exponential technologies that have potential for catastrophic consequences.

If you'd like to know more about the importance of technology in the actuarial profession, please see this detailed 35-page whitepaper by Syed Danish Ali "The Exponential Actuary[6] of the Future" to satisfy your curiosity.

CONCLUSION

All of this sounds like science-fiction right now, given that we are still struggling with human problems such as economic collapses, poverty, inequality, and natural and man-made disasters. This is why it would be useful to take heed of Amara's Law, which states, due to the exponential nature of technological change, "we tend to overestimate the effect of a technology in the short run and underestimate the effect in the long run." No one is immune from AI; every field is affected. A specter of uselessness is haunting all of us; not only actuaries but every profession from data science to those creating the AI itself.

Whatever the future brings, we must understand that technology alone won't be our savior. We need to guide it to human-centric and ethical usage, and create the necessary social structures so that we can benefit from technology instead of being ruined by it. ■

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Endnotes

1 How Augmented Reality Will Overhaul Our Most Crucial Industries; Peter Diamandis; Singularity Hub; Available at: https://singularityhub.com/2019/09/27/how-augmented-reality-will-overhaul-our-most-crucial-industries/

2 Lapetus homepage at: https://www.lapetussolutions.com/chronos/

3 SingularityNET homepage: https://singularitynet.io/

4 5 Big Breakthroughs to anticipate in 3D printing; Peter Diamandis; Singularity Hub. Available at: https://singularityhub.com/2019/04/08/5-big-breakthroughs-to-anticipate-in-3d-printing/

5 Tim Urban Wait but Why; Neuralink and the brain's magical future; Available at: https://waitbutwhy.com/2017/04/neuralink.html

6 Deloitte The Rise of the Exponential Actuary; Available at: https://www2.deloitte.com/content/dam/Deloitte/global/Documents/HumanCapital/gx-exponential-actuary-pov.pdf

SOCIETY OF ACTUARIES
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Kinky Business

Nonlinear Relationships in Linear Models

By Nick Hanewinckel

Most of those who build predictive models know the power of the generalized linear model (GLM). These models allow for nonlinearities between regressors and response via their link function. However, the underlying relationship between the regressors and the transformed response is still forced to be linear.

A common technique to overcome this forced linearity is engineering predictors—especially the popular technique of building splines. However, the decision of how to engineer these predictors is largely in the hands of the modeler and can be difficult to optimize.

Fortunately, there are models that use supervised methods to find the best nonlinear shape for the predictors. Two of these are generalized additive models (GAM) and multivariate adaptive regression splines (Earth).

This article will explore the theoretical background of the two and compare their results in a simulated mortality example. Readers are encouraged to research the technical underpinnings of their favorite model, as this article is too short to cover their full depth.

GAM MODELS

A GAM model is one where the predictor depends linearly on unknown "smooth functions," often referred to as just "smooths." Splines are just one particular type of univariate smooth function. This model seeks to estimate the optimal smooth functions in a supervised way, as well as to estimate the coefficients. These smooths can be used in the GAM atop a variety of model structures including, but certainly not limited to, the GLM family.

Given that there are a wide range of theoretical smooth functions, GAM is a very broad model class (as opposed to Earth, which only has one specific smooth function, as we will see). Smooths can be specified as splines (as described above), tensor products (multivariate interactions), and may be further partitioned by factor variables.

R's *mgcv* package and Python's *InterpretML* are popular for their respective languages. However, even these two packages differ in their approaches. With the wide sea of GAM models, users should research available packages and the approach used for their particular underlying model type.

The fitting of the smooth functions themselves take on a variety of techniques. In the packages above, *mgcv* uses a rank-reduced framework and *InterpretML* uses boosting.

In addition, GAM allows extension to a variety of model families outside those available to a GLM. The most notable from an actuarial perspective are likely the Tweedie distribution (P&C—frequency/severity) and Cox Proportional Hazards (Life—Survival).

Due to the complexity and open-ended nature, these models may take a relatively long time to fit. Fitting algorithms may vary due to the model family underlying the GAM (or even the particular GAM package used). Users may want to think about ways to boost efficiency. Besides running in a parallel process, adjusting parameters and simplifying formulae may lead to reduced runtime.

GAM allows extension to a variety of model families outside those available to a GLM.

EARTH MODELS

You may be wondering why we refer to these models as "Earth" when the acronym for Multivariate Adaptive Regression Splines does not spell the word "Earth." This is because MARS is a trademarked model licensed to Salford Systems. The open-source variety (including R package) is often called *earth*.

Earth's model takes the form:

$$\widehat{f(x)} = \sum_{i=1}^{k} c_i B_i(x)$$

Conceptually, we can think of Earth models as those that find the knots in our prospective splines (Basis Functions—Bi) in a supervised manner. To be able to do this efficiently while also solving for coefficients (ci), Earth uses special splines referred to as "hinge" functions. For simplicity, let's just say that these are hockey stick or ramp shaped. Their products (interactions) can be nonlinear (as opposed to just piecewise-linear).

While we will not go through the minute details of the fitting algorithm, suffice it to say that Earth fits in a vastly different manner to a GAM. The nature of the hinge functions gives Earth the ability to quickly fit the hinges with a least-squares update technique.

A COMPARISON

As mentioned, GAM encompasses a wide range of models making a direct Earth/GAM comparison tricky. However, there are some general ideas that are important, especially in the context of the popular R packages (Earth, mgcv).

- GAM models have a wider variety of smooth functions (including multi-demensional tensor product interactions), hence they may take significantly longer to fit. In the use case below, Earth models took ~2–5 minutes to fit (depending on degree) whereas GAM took over 20.
- Earth models will evaluate interactions up to their "degree" argument; GAM requires interactions to be explicit (by tensor product of continuous variables or using the "by" argument for a factor).
- While GAM has a wider family of models to fit, some (like Tweedie) are available to Earth (often by also using the mgcv package in R). Without the mgcv package, only the GLM family is available to Earth.
- Both functions have a variety of tuning/penalty parameters to explore, which are too numerous to cover here in depth.

USE CASE

To see these model forms in action, I have set up a brief use case in the Life Insurance context. There are a variety of actuarial uses, but mortality often works well with a poisson model, which are simple for both model families here. I have written this in R, though as mentioned, both model forms are available in Python.

An important note—the intent of this use case is to provide a simple example to show functionality and anticipate next steps. This does not represent an ideal model or model-fitting procedure. To say this another way: for now, we care more about how the *smooths* fit vs. how the *model* fits.

Data for this comes from the publicly-available ILEC data set: *https://www.soa.org/resources/research-reports/2019/2009-2015-individual-life-mortality/*

I have made this code available on github: *https://github.com/hanewinckel/KinkyBusiness*

DATA PREPARATION

We read-in the large ILEC dataset using the data.table package for efficiency. To make things even faster, we include only term policies within their level term period that have a "preferred class" designation and a valid exposure. We restrict this to ages 35–75. Next, we engineer a simple "class proportion" to express risk class relative to the number of classes. Then, we make a log-Exposure to fit in the poisson framework. Finally, we hold out the most recent calendar year for a test set.

Users playing along at home may want to tweak my code even further to reduce runtime and/or satisfy memory constraints.

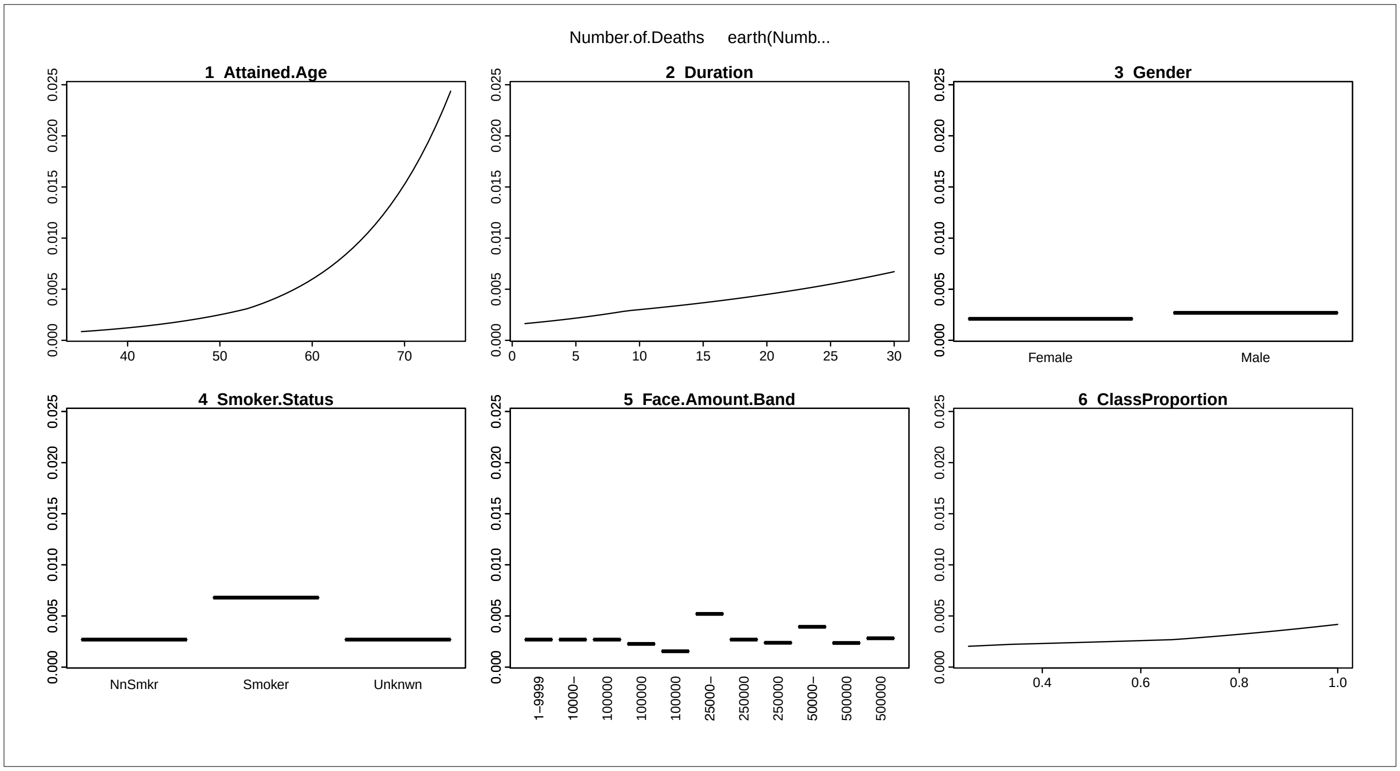
FITTING EARTH MODELS

We fit two relatively simple Earth models. We don't have to specify any smooth functions ourselves (splines) and we leave the model to find statistically meaningful interactions. Our two models differ only in their degree: modelEarth1 is degree 1 (no interactions), and modelEarth2 is degree 2 (considers two-way interactions).

Degree One Model

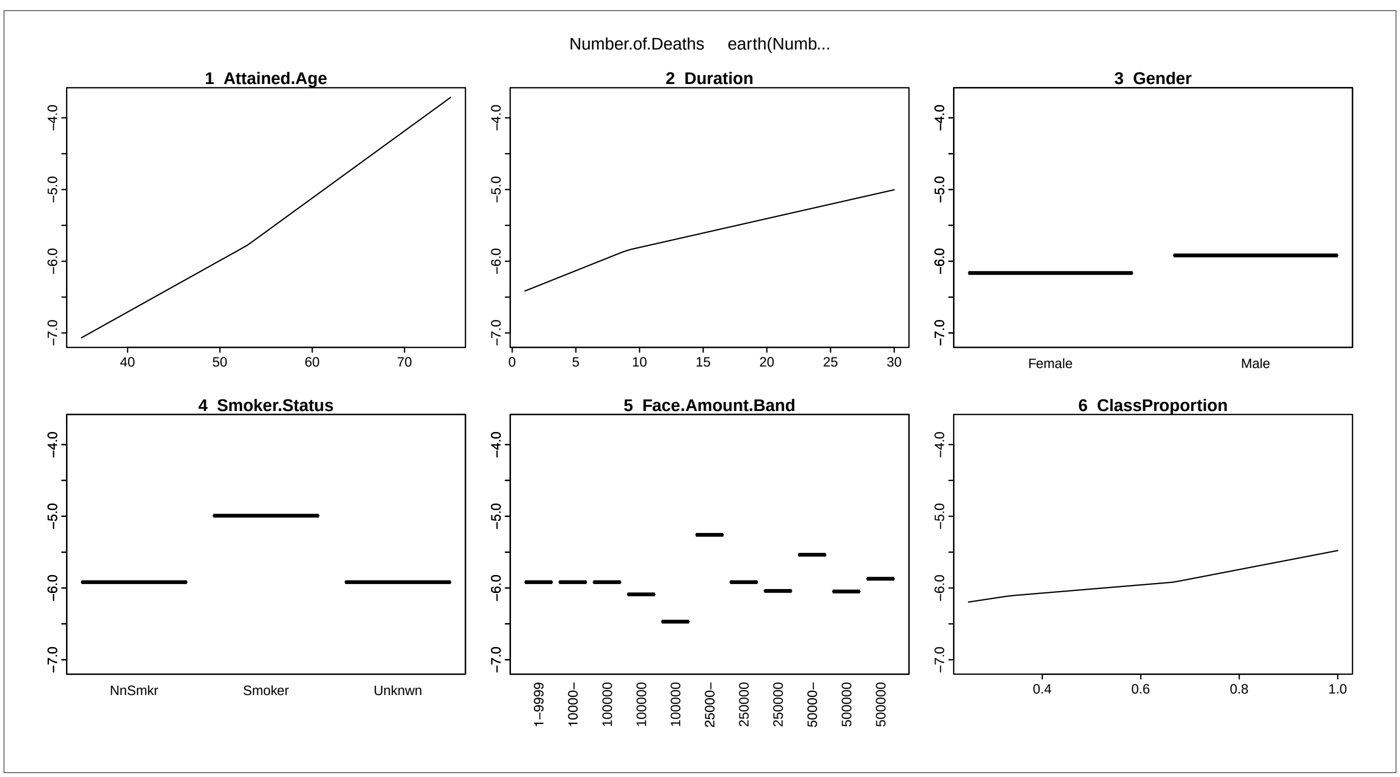
Let's look at the trademark hockey stick kinks that the rigid "hinge" function makes in this simple one-variable case (See Fig. 1).

Figure 1
Degree One Model



Now wait—that doesn't look like any hockey stick I've ever seen! But let's remember: one of the neat tricks of Earth is that the response has had a GLM (poisson-log) transformation. Let's plot these when applying the inverse (See Fig. 2).

Figure 2
GLM (Poisson-log) Transformation

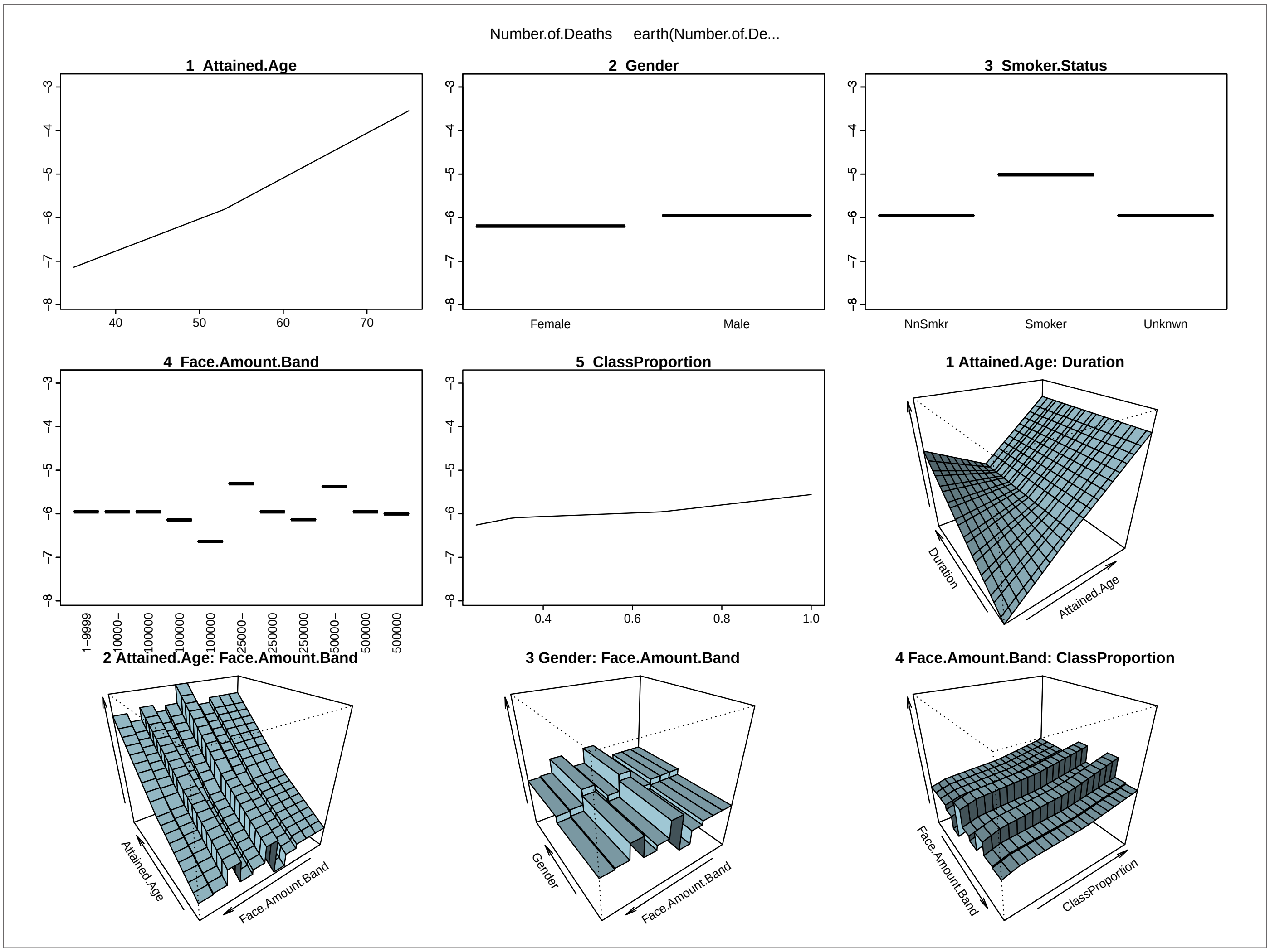


So, now they are more hockey stickish and we also see how subtle this smooth can be (particularly with multiple hinge points).

DEGREE TWO MODEL

Now we change nothing except the argument degree=2. This model fits better (trust me), which I only point out so that we can free our minds to look at the smooths themselves (with the inverse transform already done) (See Fig. 3)

Figure 3
Degree=2



Now we can see how the smooths are formed under interactions (1 Attained.Age:Duration) with factors (4 Face.Amount.Band:-ClassProportion).

FITTING A GAM MODEL

GAM requires a bit more thinking to write the call to the model function. Fortunately, Earth has shown us which interactions make for promising smooths.

I can see, for example, that Attained Age and duration have important interactions. So, I set up the regression equation with `te`(…) which is a full tensor-product, including the original regressors. It is analogous to saying `AttainedAge*Duration` in more familiar function forms. There is also a `ti`() smooth which only contains the interaction that I could have used if AttainedAge and Duration had already been stated in the formula. This is analogous to `AttainedAge:Duration`. I use the "by" argument to calculate these smooths distinctly by gender. This accounts for the different mortality behavior by gender.

Since a more complex model would take (far) longer to run, I trusted that the above multivariate smooth would account for most of the gender effects. For my other numerical predictor (ClassProportion), I simply used `s`() for spline. I declined to calculate this by FaceAmountBand, even though the chart above indicates that is a meaningful interaction. This was mainly done to speed the model and prevent overfit. But you can bet that in a "real" application, we would want to test this.

GAM SMOOTHS

The smooths for GAM are much more open-ended than for Earth. Let's see how the particular smooths and interactions look. We should expect them to look much less "sharp" than an Earth Model (or continuously differentiable, if you like to be technically accurate) (See Fig. 4 and 5).

Figure 4
Smooth for GAM

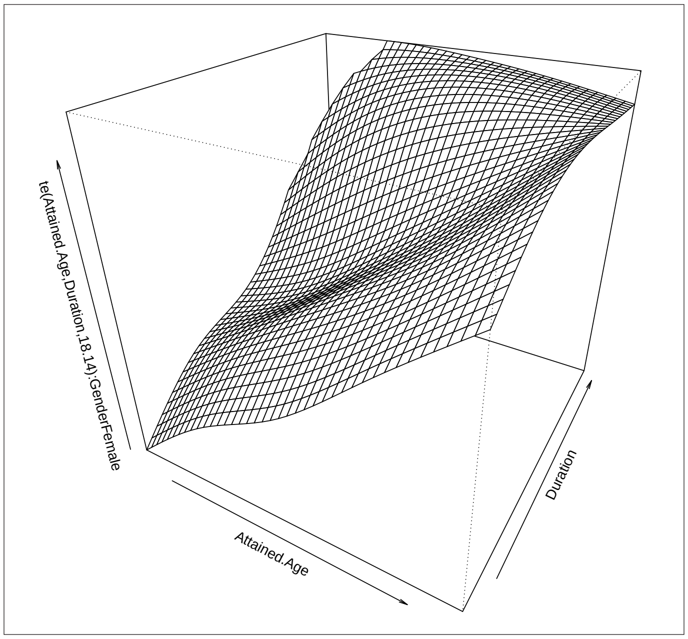


Figure 5
Example of the 2d Age/Duration Smooth Calculated by Gender (Female Shown)

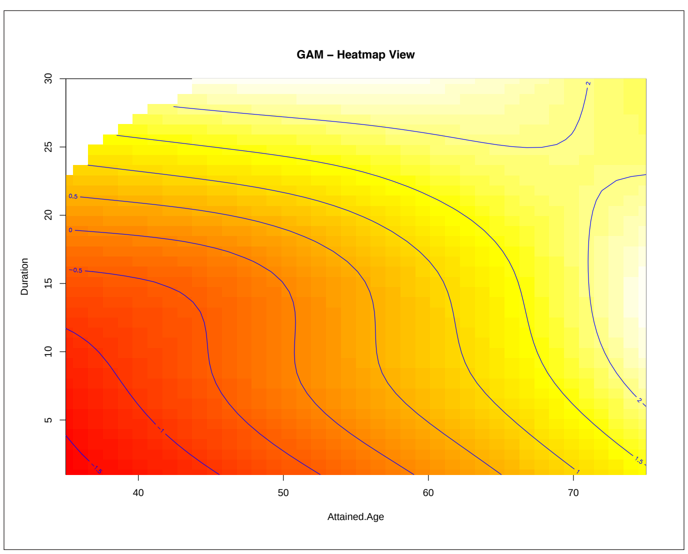
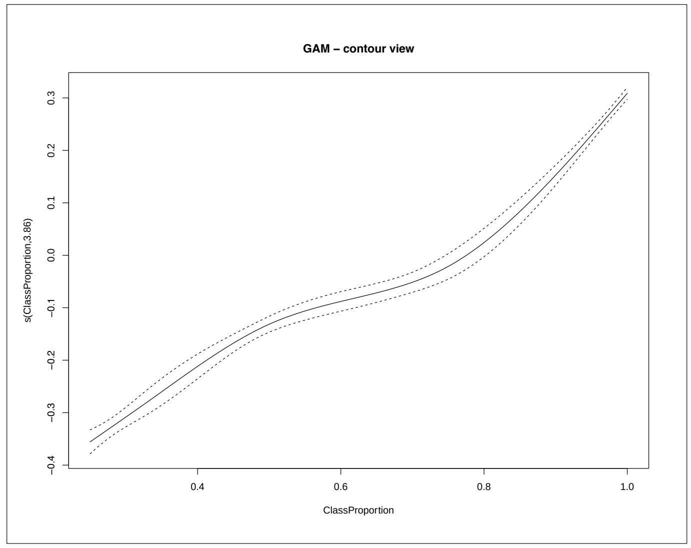


Figure 6
Example of the 1-d Smooth (Spline) for ClassProportion



MODEL COMPARISON

While these models weren't designed to be optimal, it is interesting to note the results given the smooth functions we have just examined (See Fig. 7).

Figure 7
Results of Smooth Functions

testSet	ModelEarth1ExpectedDth	Earth1AE	ModelEarth2ExpectedDth	Earth2AE	ModelGAMEExpectedDth	GAMAE
FALSE	61,566.00	100.00%	61,566.00	100.00%	61,566.00	100.00%
TRUE	22,617.32	96.11%	21,852.65	99.47%	22,437.28	96.88%

From this, we can see that the degree-2 Earth model performed substantially better than a single dimension Earth model. This is to be expected as modeling interactions is one of the benefits of moving to this model type. The 1-d model may suffer from underfit given that its 2-d counterpart was not over-specified.

We should be careful not to draw the conclusion that the GAM did "poorly" just because its holdout A/E was closer to Earth1 than Earth2. There was little to no optimization on this model, and it was partly modified to run quickly. Rather, both models should be experimented with. We'd want to explore most meaningful variables (perhaps taking a look at Earth's ranking of significant smooths), but in addition, we'd want to look at the penalties and other parameters available to determine the smooths. Don't forget—figuring out *which* smooth functions to use is part of GAM's job; Earth always uses hinge functions.

CONCLUSION

Both packages are great tools for modelers to have in their arsenal. With so many potential uses, it would be impossible to universally prefer one over the other. I invite all modelers to play around and see what meets their actuarial needs. Both models are great tools to have, but in the words of LeVar Burton, "you don't have to take *my* word for it!" ■

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Take note! Plans are currently underway for the 2020 Predictive Analytics Symposium. The SOA is commited to moving forward with the fall meetings with a virtual component. Nothing is more important to us than the health and safely of our attendees, partners, suppilers, and employees. We look forward to sharing more information regarding this year's program with you in the coming weeks.

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