DATA SCIENCE AND VE - IS THERE A MARRIAGE?

ROBERT ORLEAN, CVS - ORLEAN TECHNICAL SOLUTIONS

Abstract

This paper examines the Value Engineering Methodology through the lens of the methods of machine learning, artificial intelligence and expert systems to suggest how these might marry. It intends to be a provocative paper about what might be possible to bring together VE and these powerful but complex methods.

It proposes several avenues of VE process innovation but recognizes that this will be a difficult journey for our community. Embracing this marriage will demand new methods, tools and interactions between SAVE International, its members and users of the Methodology. But it is a journey on which we must embark to remain relevant in the next 70 years of our Society.

Introduction

Continuous and rapid progress is being made across the industrial, scientific and commercial spectrum in the use of Data Science methods. Expert Systems, Artificial Intelligence and Machine Learning are now routinely applied to dramatically increase value in a host of ways.

Without any doubt, it behooves the VE community to examine how Value Engineering can leverage these methods to our advantage. We must do this to remain relevant in the context of evolving societal expectations and demands for speed, accuracy and convenience, while balancing the needs for confidentiality and cost effectiveness.

This paper takes a view of potential innovations in the VE methodology and Post VE value-capture efforts for a few of the well-known data science technologies. No doubt, other methods exist or will emerge in the future which can equally add value to our methodology.

Innovation is in our Genes

Humans are genetically inclined to innovate. Since the dawn of man, we have continually created advances to improve our condition, and there is no end in sight to this progress. Value methods are not exempt from or immune to this bent for innovation, and we would be remiss if we did not routinely and deeply examine potentials for improvements using what becomes available to us through time.

To put this in context, since the establishment of the Value Methodology in the mid-1940s, we have seen a mind-boggling amount of innovation. Focusing only on computing and digital methods, in the 1940s when the Value Methodology was conceived, computing technology was in it infancy we saw:

- The first 1st digital computer to solve linear equations.
- The invention of transistors
- And for context, in other areas:
    - Instant photography
    - The dawn of the nuclear age
    - Microwave ovens
    - By accident!
    - Color TV

- o Duct Tape
- o Penicillin

Moving forward one decade we truly entered the Age of Technology as we saw the development in the 1950s of:

- Video tape recording
- Hard drives
- Lasers
- Microchips

Fast-Forward (or should that be Skip?) to 2019, and we see a wholly different technology landscape, primarily driven by computing power. Not only is there an Internet that connects over 3 billion people on Earth to an inconceivable array of knowledge, but computers are almost daily capable of incredible feats of analysis and prediction.

We experience on a daily or even hourly basis multiple interactions with computers that perform an array of both simple and very complex tasks quickly and accurately. These feats are accomplished through combinations of technologies that include amongst others:

- Expert Systems
- Artificial Intelligence
- Machine Learning

And this is to say nothing of the host of other incredible technological advances in such areas as robotics, materials science, visualization and 3D printing, to name just a few and to which we could add innovations in commercial transactions, finance, etc.

How has VE changed in this same period? Not very much (although this is not by implication a bad thing). Yes, we may leverage the same computing technologies to reduce or eliminate some of the clerical effort demanded of our methodology or to expand the suite of solutions to apply, but our core methodology is still rooted in manual function analysis, team dynamics and sound decision making.

TRENDS AND EXPECTATIONS

As a Value Engineering community, we cannot ignore the environment around us, or as Genrich Altshuller, the creator of TRIZ called it, the Super System. (More on TRIZ later). Indeed, Altschuller would posit that using these Super System elements evolves us to a more "ideal state", analogous to increased value delivery.

These evolutions in computing power and data science that we experience in our daily lives automatically create expectations of the VE Super System. We now routinely expect high accuracy, quality and speed in most areas of our interactions with technology. We would be remiss if we thought that these expectations will not or do not apply equally to Value Engineering.

In particular, we should ask and answer how Data Science methods can help our methodology to grow and thrive in the future. The following section examines some of the current data science methods to lay a foundation for what may be leverageable by our community.

DATA SCIENCE METHODS

Before we examine more recent data science methods, let's take a look at a pre-computer-age method that nonetheless established some important data mining concepts and made them fairly usable. This example may provide a bridge to more sophisticated tools were we to embrace Data Science in Value

Engineering.

TRIZ

Surprisingly, like the Value Methodology, TRIZ was also conceived in the 1940s, and includes some tools that are the result of extensive data mining to improve the innovativeness of technical solutions. Without entering an in-depth description of the very multi-faceted TRIZ theory, there are at least two elements that pre-date data science methods:

Contradictions Matrix

First, let's consider the most recognizable element of TRIZ - the Matrix of Contradictions. This matrix lists on its symmetrical axes features to preserve and features to improve to evolve a system towards increasing value. These features are by design expressed in very general or abstract terms such as Temperature, Loss of Time, Weight of a Moving Object, etc. See Figure 1 below.

By selecting on the matrix axes a feature of a design that requires improvement without degrading an also-selected other feature, the user then refers to the intersection of in the matrix. At the intersection the user finds a list of a few "Inventive Principles" - abstract descriptions of known solutions that allow the desired feature to improve without degrading the feature to preserve.
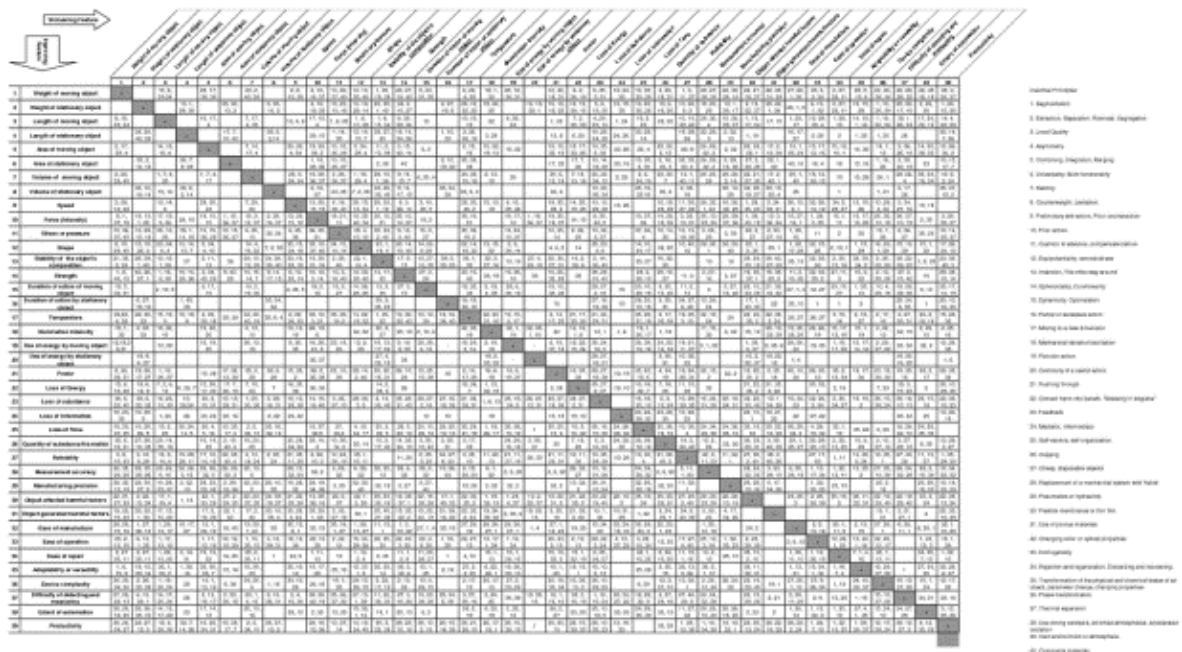

Figure 1 - TRIZ Contradictions Matrix

The interesting insight from a data science perspective is that the Inventive Principles listed in the Contradictions Matrix are those that through extensive research and cataloguing have been found to be the solutions known statistically to be the ones most commonly applied. In fact, the recommended Principles are listed in descending order of frequency of use.

In other words, by data-mining enough inventive solutions across multiple industries, the matrix prompts users to examine how the most successfully used principles might also apply to their unique situation.

It is also worth noting that the matrix continues to evolve with more research, and is far from static.

Trends of Evolution

Second, another dimension of TRIZ is the Trends of Evolution. These trends describe known "trajectories" of development of systems over time. As with the inventive principles, these trends were derived through extensive observation and study across many technologies. And as before, these trends provide users with interesting evolution paths for existing designs which may not have occurred to design teams.

For Value Engineers, consider the implications if we were to similarly aggregate across the universe of FAST models created by our community over the last 70 years the best means to satisfy functions in a given situation. Then, consider the potential of this aggregation if we could also capture the evolution of these solutions over time. Doing this would create an analogous tool to the TRIZ Contradictions Matrix and Trends of Evolution.

So while pre-dating the computer age, the data-mining that under-pins TRIZ demonstrates the value seeing and delivering helpful trends to innovation problems, albeit through very manual data extraction and prediction. Artificial Intelligence takes this concept much further.

Expert Systems

Next, let's consider Expert Systems. The earliest Expert Systems date back to the mid-1960s. At their core, Expert Systems are a collection of IF:THEN rules that are applied to user inputs and which embed data from which to extract recommendations. These rules aim to capture the human decision-making process in a variety of conditions.

Expert Systems make complex user decisions accurately without the user having to be an expert. What Expert Systems don't do is learn. Instead, they apply the same embedded IF:THEN rules for every task.

There are many examples of Expert Systems:

- Preparing US tax returns with limited accounting expertise
- Diagnosing illnesses from an input of symptoms
- Creating complex yet accurate designs from limited information
- Monitoring sensor data to foresee performance problems

While relatively simple, Expert Systems are very useful. Considering one Expert System well-known to US tax payers, TurboTax is a widely used tool for preparing individual tax returns. Users are prompted by the program to enter specific data about earnings, the number of dependents, etc., and the IF:THEN rules in the program are applied to create specific outputs based on the rules embedded in the program from the US Tax Code. In the case of TurboTax, the output is a file-able tax return,

Interestingly, this program is so well-regarded that tax payers trust the accuracy of the tax returns on penalty of fines and perhaps even jail time.

Of course, we can only imagine the resistance to this concept put forth by tax accountants. More on this later.

Disadvantages of Expert Systems often cited are that the acquisition of the knowledge that creates the IF:THEN statements demands intense focus by human experts, and is tedious. But while true, this can also be seen as an advantage, particularly in industries with aging demographics (including ours, I suspect). In these cases, the creation of expert system rules provides a means to capture and codify years of experience for future generations.

For Value Engineering Practitioners, Expert Systems can potentially help to systematize and standardize much of the framing and decision making processes in our methodology, potentially improving quality and reducing variability of application.

Artificial Intelligence

Artificial Intelligence, like Expert Systems, aims to simulate human behavior with computers. What is

different is that in AI, the input data sets are not finite (such as the content of the US Tax Code for TurboTax), but rather seek to find trends by combing through masses of seemingly un-related information to find relationships that are not readily visible by other means. True AI then uses these relationships to make predictions and recommendations about future events or actions.

There are many applications of AI technology with which we all interact daily. Notable examples include making purchases on Amazon, which uses your transactions to discern buying trends and recommend additional purchases with remarkable accuracy. In fact, all search engines attempt to do the same thing with each enquiry, honing returned results with each query.

As another example that is less visible to us, but extremely powerful are AI analyses that plumb human emotions to maximize the value of advertising revenue from media content (TV shows, movies etc.) through highly complex analysis of plot lines, character development and outcomes. Again increasing in complexity, the automobile manufacturer Lexus recently release a commercial for its cars that was entirely scripted by AI.

What enables AI to work well is access to data. Lots of data. That is why Google, Facebook, Amazon and Microsoft in particular are major players in the field of AI. Without lots of data, predictions are less accurate, and therefore less valuable. It is also why it is hard to be a successful start up in the field of AI.

But is AI beyond the reach of the Value Engineering community? Perhaps not. What we have in abundance is data - some 70 years of very detailed information about exactly how things work (FAST models), the value of specific functions to users (Dimensions, Value Rankings), ideas that are accepted or rejected (both provide useful insights), and their value. Further, we have this data across most industries.

Machine Learning

Taking a step into more complex technologies than Expert Systems and Artificial Intelligence, the idea of Machine Learning is to enable a computer to progressively improve the quality of results by looking at past data and learning from it, without the need for human intervention. This idea began in the late 1950's.

With Machine Learning, computers no longer need to receive an 'input commands' to perform a task, but rather 'input data'. From this input, Machine Learning creates a model to analyze the scenario based on previous experiences captured in the data. And in turn, the computer is then able to formulate decisions.

As a simple example, a machine learning program looks at what e-mail senders' messages routinely sent to a spam folder or deleted and infers from those actions that anything coming from this sender is probably spam. Then, the spam filter on your email is automatically updated with this information and you don't receive messages from this sender

A much more dramatic example is AlphaZero - a program than recently mastered the game of chess, not by being highly programmed with a myriad of rules and applying these to millions of possible outcomes, but rather by learning from past successes and failures to recommend moves.

Remarkably, AlphaZero was able to master the game in just four hours, despite not being programmed on how to win.

POSSIBLE IMPLICATIONS TO THE VE METHODOLOGY

So what are the implications of these incredibly powerful technologies to our Value Engineering methodology and community? Possible applications range from the tactical to strategic, with increasing value impact and complexity.

While we are likely a long way from replacing VE teams and the power of the human brain with computer programs, it may be possible to augment our methods. For example, we can easily foresee the creation of Expert Systems that:

- Accurately and consistently frame a value engineering problem
- Distill specific industry value drivers into an accurately ranked and scored set of problems to solve through a series of focused questions.
- Apply rules of knowledge, experience and personality to recommend an ideal VE team make up for optimum results
- Recommend the optimal level of abstraction of FAST models to match the VE challenge at hand.
- Build FAST models and perform value analysis of functions in each model. (In fact, a very similar capability to this already exists in some TRIZ-based programs).
- Standardize the evaluation of alternative concepts
- Automatically develop a summary presentation of results, implementation plans and follow up tracking systems.
- Archiving study results for analysis by AI and Machine Learning applications.

Going deeper into Artificial Intelligence tools, it should be possible to:
- Compare proposed VE projects with similar past challenges within and across a company or industry and highlight previously successful innovation paths.
- Recommend alternative solution paths that would otherwise not be considered from outside a company or industry
- Augment ideation with adopted, successful recommendations from past studies, catalogued by function. These might look across other company results, or across an industry, or across the universe of solutions that satisfy a particular function.
- Accurately assess ideas against value drivers and technical maturity
- Analyze the creative performance of VE team members and examine why particular individuals were more creative than others.

And finally, using Machine Learning methods, we may be able to
- Assess ideas by likely implementation risk and expected actual performance in a given situation.
- Take the highest ranked ideas for a project and by machine learning recommend the optimum combinations of these to achieve particular alternative goals such as lowest cost, shortest delivery, lowest risk, etc.
- Learn from history which ideas yield the most benefit in reality and understand why this occurs.

Looking further downstream from these, it is very conceivable to link the results of VE studies directly into other systems, and ultimately to a "Buy Now" capability that initiates execution. Of course, there are no doubt many more ideas for the application of these and other emerging methods in the future.

CASE OF ACTION

What could these applications mean for our Value Engineering community? Certainly, we cannot escape the evolution of expectations for increase speed, accuracy and efficiency mentioned above. And so superficially an embrace of data science tools in the VE methodology would align with the evolving expectations of our user community.

Notwithstanding these expectations, there are also numerous strategic and tactical advantages to be grasped with the embrace of these technologies.

Tactically, some of these ideas would enhance the quality of ideas generated in a VE study, improve the

selection of ideas that add value, increase the likelihood of actual value capture and help eliminate some of the more routine elements of a VE project. They may also remove some of the variability from the delivery of VE studies that is driven by Sponsor, team and facilitator capabilities. Overall, these alone would improve the value of VE engagements.

More importantly there are multiple strategic reasons for adopting a path of embedding advanced data science tools into our methods. In particular, we must remain a viable and competitive methodology as data science capabilities rapidly evolve around us. Further, we have an enormous, as yet untapped resource in 70 years of VE study data, that if examined, would yield insights that Google, Amazon and others cannot hope to create.

Finally, the demographics of SAVE International members and CVSs may like much of the national demographics be aging. Adopting an aggressive approach to capturing our collective knowledge and experience will be vital to sustain our capabilities into the future.

IS IT POSSIBLE?

Whatever marriage we see between data science methods and Value Engineering, it will not be a simple undertaking. There are and will be many barriers to overcome to gather the data that we have, fund, develop and maintain any data science tools across our society (or indeed within corporate VE practices).

In particular, maintaining data confidentiality will be a major challenge, as this consideration is already becoming the subject of much publicity and even legislation, and given the competitive nature of VE approaches and ideas generated.

Also, on a personal level, those who have been successful in the past using the current Job Plan may not be those who will be needed to be successful in the future. Adoption of new methods and tools will be threatening to many in our community today and will garner much resistance.

However, these barriers can be overcome with a clear and compelling vision of our direction and its value to our society and the users of Value Engineering. Clean ownership of data science initiatives will also be paramount.

We have many of the essential ingredients to success already. We have

- A proven approach that is fundamentally sound

- Mountains of data to mine

- Common problems to solve in each industry that bracket the scope our challenges

- Multiple other data science applications already adopted and in use in our lives

- A willing and adoptive user base that will likely embrace sound changes

CONCLUSIONS

To move forward, we will first need to create a vision of how SAVE International will position itself with respect to data science. Therefore, we should embrace the challenge by asking how the Value Engineering methodology should rise to these Super System expectations in the next 20 years. Creating a 2040 Value Vision around these inevitabilities will help guide us towards the future of our methodology.

This will require the formation of an exploratory group in our Society to fully understand and craft this vision and to plot a path forward. This group must comprise both experts in Value Engineering and in Data Science.

Taking a long view, success in this endeavor will mean that our Society remains a highly competitive, relevant and viable methodology for innovation and value delivery. Failure will likely mean that other data science methods will eventually overtake and supplant us.

The choice is ours to make.