RECASTING THE ROLE OF BIG (OR LITTLE) DATA:

OPTIMIZING REVENUE AND RESOURCES BY TRIGGERING UNIQUE INSIGHTS

A White Paper Series by:
Susan Bennett & Barry Hix

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INTRODUCTION TO A WHITEPAPER SERIES

Accelerated Vision invites you to join us in our quest to deliver on the promise of Big Data. Our team is producing a set of white papers and blogs aimed at answering these questions:

- How do we use Big (or Little) Data to answer the questions we care about?
- What assumptions in our healthcare or life science organization need to change before "Big Data" or "Little Data" can be a reliable source of power?

With this series of papers, we invite you to engage in a meaningful dialog about Big Data and, more importantly, the path to arriving at unique and compelling insights using Big Data.

THE JOURNEY TO CONTEXT

About 20 years ago, I (Susan) was working for a multinational oil services company as a wireline field engineer. We would drive hundreds of miles with our truck and crew to a remote rig. And then we would spend hours and sometimes days lowering tools into wells recently drilled. These tools were connected with a wire into a sophisticated computer system in a truck, to take measurements along the wellbore. Our management was very good at collecting data related to safety. We had units in our car that tracked how we drove. We filed reports about near misses related to our safety en-route and at the rig.

As I looked at this information, it appeared to be trending towards a major accident. I thought someone was going to be seriously injured or perhaps die. Ultimately, I left the organization because I did not want to be that person.
A friend of mine called shortly thereafter.
She said "I heard you quit. Should I quit?"
"If you can hold out until you're fully vested, that's great. But it's not worth your life." I replied.

About 3 months later she died. She wasn't wearing her seat-belt and had rolled her vehicle coming back from the oil rig.

The data didn't say "someone is going to die". That was my interpretation: I produced a "connection-of-the-dots", which became an actionable insight that helped me to quit. But I recognized later that my own fatigue and assumptions were some of the "dots" that led me to an action (quitting) not necessarily warranted by just looking at the company data. I could also see the toll on my body that commitment to my obligations was taking.

Since then I have been on a quest for meaning about this situation: how do I look at data and the assumptions and beliefs behind its interpretation to produce reliable and meaningful action to prevent costly losses? This quest has matured over time. It began with acquiring knowledge about various data mining techniques. It graduated into the world of machine-to-machine data, linguistics, economics, psychology, and the modeling of complex systems. Ultimately, my quest led me

into designing and selling services that enabled a diverse group of multinational corporations to decrease risk and costs while increasing productivity.

Then along came “Big Data”.

BIG DATA OR LITTLE DATA CAN LEAD TO UNRELIABLE OR MEANINGLESS RESULTS

Big Data market leaders describe it across several dimensions[1] :

- Volume
- Variety (e.g., structured, unstructured, photos, videos)
- Velocity (i.e., massive data flow)
- Veracity (i.e., biases or noise)
- Validity (i.e., correctness or accuracy for intended use)
- Volatility (i.e., timeframes for data validity and data storage).

But ‘Little Data’ has an overlapping set of challenges:

- Variety
- Veracity
- Validity
- Volatility

And in **complex systems**[2] , such as our bodies, institutions or the entire medical system, both big and little data can have a lot of variables: elements or features of the problem that can change over time or across other dimensions (e.g., location).

In healthcare, we’re often dealing with ‘Little Data’: we might have a sample set of 50 patients but an enormous number of real-world variables (e.g., psychology, diet, social groups, education, economics, environmental exposures, etc.) to consider across that group. If we do not select the most important variables for answering our question over the relevant horizon of time, our data (or lack thereof) can lead to unreliable or meaningless interpretations. For instance, calcium depletion for a woman at age 60 has different implications than for a male 17 years of age.

More importantly, not selecting the most important variables of the complex system over the relevant horizon of time produces unreliable results that can lead to dangerous situations. It seems to us when managing Big Data (or Little Data) that there is a general disrespect for the limitations and constraints of our humanity and our models, which can lead to a loss of businesses and lives. It scares us.

For instance, look at AIG, which went bankrupt during the liquidity crisis of 2008. In a Harvard University paper called “The Credit Rating Crisis”, the authors discuss the mistakes that were embedded in AIG models[3] . Many relationships and feedback mechanisms in the economy were unaccounted for in these statistically based models – including the use of the models themselves – culminating in the financial crisis of 2008. These relationships included government policies, overvaluation of bundled sub-prime mortgages, questionable trading practices, compensation structures, and lack of capital holdings from banks and insurance companies[4].

Big Data doesn’t appear to be changing our thought process about complex systems. We’ve already experienced near misses and major accidents by not using Big Data effectively. Mishandling Big Data may produce the same consequences as putting a nuclear weapon

[1] http://inside-bigdata.com/2013/09/12/beyond-volume-variety-velocity-is-sue-big-data-veracity/

[2] See the Glossary for a definition of this term “complex”.

[3] http://www.nber.org/chapters/c11794.pdf. “The Credit Rating Crisis”, by Efraim Benmelech and Jennifer Dlugosz. P.1. Last sourced: January 3, 2013.

[4] http://en.wikipedia.org/wiki/Financial_crisis_of_2007%E2%80%932008

into the hands of a North Korean dictator: an unacceptable outcome. The nuclear weapon in this case is "Big Data" – a potential threat in the wrong hands. And the dictator is any human or business with any unchecked blindness to the paradigms (assumptions, beliefs) within which it operates. We will expand on this theme more fully in this paper.

HOW DO WE HELP BIG DATA PRODUCE RELIABLE AND MEANINGFUL RESULTS?

How do we use Big Data to answer the questions we care about? And what assumptions or beliefs about data in our organization need to change before Big Data can become a reliable source of power? (Note: Here and from now on we use Big Data generically to include Little Data that has lots of variables).

For example, before the launch of a new drug, the brand team cares about gaining insights into the answers to the questions below, to mention only a few:

- What is its market potential?
- What are the barriers or hurdles to adoption?

Our intention is to share with you some new ways of thinking about your data that may help you answer these questions and contribute to your organization's competitive advantage.

We describe one of these new ways of exploring data in the first set of blogs and this first white paper. They address how humans and their background knowledge and assumptions produce context: our backgrounds and knowledge act as a set of filters for organizing the data into meaningful connections and producing information from the data, which allow problems to be solved or spur effective action. Get the context wrong and everything else is unreliable. We present the following contrarian claims for consideration:

- "Data speaks for itself" is a false and dangerous notion. It can and eventually will kill your company[5].
- Context is critical for addressing complex problems.
- A deliberate production of context is required.

Below is an example of how one of Accelerated Vision's subsidiaries produced context to achieve surprising and effective business results that others could not:

An ambitious operations group within a Fortune 100 oil & gas company was working to increase oil production from existing wells. They had lots of data. And yet after about 10 years+ of experience with a certain type of treatment, they were about as good as a coin-toss at anticipating what wells would produce more oil with the treatment. **If data speaks for itself, why couldn't they anticipate what wells to treat?**

We first explored this problem and the ways that the engineers thought about the problem to understand what was fundamental about

[5] See the AIG example in the introduction to the whitepaper series

their thinking. Using the same data set they had already, we produced context and a model for identifying the wells that would respond to the treatment, demonstrating that production could be improved with greater than a 30% return-on-investment.

We didn't do this by programming the specific way the engineers were approaching the problem. This would have produced the same ineffective results. Instead, we achieved our more successful outcome by incorporating the fundamentals that are already understood by domain experts and by following a methodology for solving complex problems based on a systems dynamics modeling framework.

Our methodology includes a structured approach for examining and choosing the most important variables or influencers of outcomes, the application of our intellectual property to help both overcome the limitations of and leverage human intelligence, and a platform that can handle the enormous number of variables necessary to describe the context of complex systems.

The data did not speak for itself. We had to interpret it.

WHAT OTHER KNOWLEDGE CAN HELP MAKE BIG DATA FULFILL ITS PROMISE?

Our subsequent white papers and blogs will have the following themes:

- Have you ever considered there may be a distinction between **complicated** and **complex** systems that can help your data interpretation? Knowing our proposed distinction before you begin your analysis may help you avoid poor business decisions.

- As you examine key variables that may be influencing the problem, are you looking for **frequency** or **significance**? Knowing which to look for in what situations can be a competitive advantage.

- How do you **anticipate the bend in the trend**? What's noise and why do patterns matter for fulfilling data collection and analysis objectives for your business?

WE WOULD LIKE TO ACKNOWLEDGE THE PEOPLE WHO HELPED US PRODUCE THE SERIES.

First, thank you to the many editors who are listed within the papers or blogs. They bring multiple perspectives from epidemiology, mathematics, chemistry, psychology, systems dynamics, etc. . Thank you to Manny Aparicio, the Chief Memory Maker and one of the founders of Saffron Technology. Saffron has a powerful platform that we leverage for our solutions. Thank you to Admiral John Poindexter for his foresight and assistance in connecting us with Saffron.

And thanks to those of you who will be compelled by this series of blogs and papers to work with us to find solutions to your business challenges and increase your competitive advantage in your marketplace.

Sincerely,

Susan Bennett & Barry Hix

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DATA DOES NOT SPEAK FOR ITSELF: CONTEXT MATTERS

Pay Attention to the Man Behind the Curtain

DO PAY ATTENTION TO THE MAN BEHIND THE CURTAIN!

There is a dirty little secret that is slowly making its way to the headlines: **Big Data's promise is hype**. The promise of Big Data is that correlations across hundreds of variables will provide meaningful information and useful insights: you don't have to understand causation or have a narrative about the system under investigation. Another way of stating this is that "Data speaks for itself." In fact, it doesn't.

A recent article from The Financial Times, "Big Data: are we making a big mistake?" (Harford, 2014), described how in 2009 the Google Flu Trends team used online web search queries to monitor health-seeking behavior. The team found that "...the relative frequency of certain search queries is highly correlated with the percentage of physician visits in which a patient presents influenza-like symptoms", leading them to estimate influenza activity with a reporting lag of approximately 1 day.

It was later discovered, four years after Google's initial declaration of success, that Google's estimates of the spread of flu-like illnesses for that year were overstated by almost a factor of two compared with information from the Centers for Disease Control and Prevention (CDC).

"Data speaks for itself" is a false and dangerous notion. If accepted, this assumption could lead to business decisions that may damage, or possibly kill, your company. Any reported finding about data has some – often unnamed – process in place that was at some point generated from human input. A human designed the system to collect the data, a human designed its representation, a human analyzed it, a human interpreted it and a human produced the conclusions and decisions.

Our decisions are often based on an unknown or hidden interpretation of the way we think. Figuratively, we call the human and his/her unknown or hidden interpretations "The Man Behind the Curtain". And technically, we call the human and his/her interpretations "mental models".

A mental model is a set of assumptions about a system, its purposes, the relationships between components, and how it operates. A system can be physical (e.g. computer), social (e.g. family), economic, to name only a few characteristics. Every time we capture information from our environment and represent it in a computer or present it to someone, we operate with a set of assumptions about "what is real". Most of the time, the assumptions are not obvious. Increasingly, they are revealed through mishaps resulting in lawsuits, disasters or deaths of people and businesses. These assumptions can include:

- Frequency of equipment calibration or transmission.
- What data elements to include and how to represent them in a database.
- What relationships or trends in the data are meaningful to resolving the problem.
- Why any of the assumptions matter.

Remember the key promise of Big Data – that correlations across hundreds of variables will provide meaningful information. But there is a Man Behind the Curtain holding plenty of assumptions collecting the data and making the correlations. And that means that Big Data can have unanticipated results, making its promise unreliable.

You may remember the story of the Wizard of Oz. The Wizard of Oz believed he was the only man capable of solving his subjects' problems. When Dorothy and her friends went to see the wizard, all they heard was a disembodied voice whose pronouncements seemed to be magical. But Dorothy and her buddies eventually revealed that the Wizard of Oz was not magical at all, just a man behind a curtain with his own set of assumptions and beliefs.

> **The Wizard**: "Do not arouse the wrath of the great and powerful Oz! I say come back tomorrow!"
>
> **Dorothy**: "If you are really great and powerful, you'll keep your promises!"
>
> **The Wizard**: "Do you presume to criticize the great Oz?! Think yourselves lucky that I'm giving you audience now instead of 20 years from now! "

The characters begin to notice a man behind the curtain.

> **The Wizard**: "Pay no attention to the man behind the curtain!"
>
> **Dorothy**: "Who are you?" as she speaks to the man behind the curtain.
>
> **The Wizard (the man behind the curtain)**: "Oh, uh... I am the great and powerful Wizard of Oz"
>
> **Dorothy**: "You are?! I don't believe you."
>
> **Wizard**: "I'm afraid it's true, there is no other wizard except me."

There was no magical Wizard of Oz. There was an ordinary man from Nebraska behind the curtain. The Wizard of Oz was just the voice of a man. And like the Man Behind the Curtain from Nebraska, who pretended to be a wizard to solve his subjects' problems, many companies think they can solve their clients' problems, as well as their own, through the disembodied voice of Big Data. Pretending to be a wizard through Big Data has challenged their ability to keep their promises, as we shall see next.

BEWARE OF THE DISEMBODIED VOICE OF BIG DATA

As mentioned at the beginning of this introduction, a similar Wizard of Oz situation occurred several years ago, when Google – the Man behind the Curtain with the assumptions and beliefs – pretended to be a wizard.

The Google Flu Trends team found some interesting correlations. Ginsberg concluded that "Google web search queries can be used to accurately estimate influenza-like illness percentages in each of the nine public health regions of the United States." (Ginsberg, 2009). Another article supported Google's results, "...It turns out their system tracks the CDC data quite nicely."(Madrigal, 2009).

It was just a matter of time before we would see the incompleteness of their thinking. Big Data couldn't keep its promise. When compared with CDC's information several years later, Google's estimates were overstated by almost a factor of two.

How did this happen? Google used 'an automated method' of discovery requiring no prior knowledge about influenza. Doesn't this sound magical, as if it were coming from a "disembodied voice". Where's the man behind the curtain with his assumptions and beliefs?

But there were some small caveats in the original Ginsberg paper:

- "... we cannot be certain how search engine users will behave in such a scenario", referring to users' behaviors during pandemic events
- "... correlations we observe are only meaningful across large populations."
- "An unusual event, such as a drug recall for a popular cold or flu remedy could cause... a false alert."

So Google did make assumptions.

By stating "correlations we observe are only meaningful across large populations", Google left the impression that their model was "theory-free", according to the Financial Times (Harford, 2014).

But stating that something is "theory-free" is a theory.

In other words, there was a general failure to acknowledge the existence of the Man behind the Curtain. There was a theory and Google supported it with the following premises:

- Correlations are meaningful across large populations;
- and the discovered correlations are meaningful.

> Nothing we invent as humans is 'theory-free'. Nothing. There is no magical Wizard of Oz.

The Financial Times article rightly points out that the concept that "data speaks for itself" is utter nonsense. Numbers do not speak for themselves. Ever. When we assume they do, mistakes can be made, even costing people their lives. Consider the infamous Space Shuttle Challenger. If numbers were obvious, then the answer to the question "Will the rubber O-rings fail catastrophically tomorrow because of the cold weather?" would have been an obvious "yes". They had the data, but not the proper presentation of it (and perhaps not the organizational culture) to interpret it effectively (Tufte, 1997).

WHY IS AN UNDERSTANDING OF POSSIBLE CAUSES AND EFFECTS REQUIRED?

Behind the "theory-free" label was the assumption that we don't need to know what causes what. But we do.

We do because we tend to assign too much weight to the data that is available. Without having a base of theory about what causes what, we are:

a) Flummoxed about how to represent the data that is available, and

b) Blinded to what might be missing that could affect what we're seeing.

When we do have an understanding of possible causes and effects, we are then able to make assessments about what data might be missing. An understanding of possible causes and effects is a mental model. And even if we don't have an understanding of possible causes and effects, we are still using some sort of mental model to collect and interpret the data.

By not keeping that mental model in constant view, we forget it's there. The data appears 'magical' like a disembodied voice (i.e., the Wizard of Oz), and it becomes very difficult to challenge. It's as if the data is the truth as opposed to a partial representation and interpretation. And we don't know whose truth it is.

THE NEED FOR VISIBILITY: MORE ON MENTAL MODELS

A **mental model** is a construct that is widely accepted in psychology and philosophy. Some people describe it as a collection of typologies for categorizing experience (Sterman, 2000). Charlie Munger describes it as a framework for gathering, processing and acting on information (Munger, 2005).

For example, up to the early 1980s, the focus for helping ameliorate diabetes was on carbohydrates. People were told to avoid simple carbohydrates and the food that contains them, such as sucrose (fruit juice, soft drinks), fructose (fruits) and lactose (milk) because the accepted mental model was that they rapidly raised blood glucose levels. And they were told they could eat complex carbohydrates – breads, grains, pasta, rice, corn, legumes, potatoes and vegetables - because it was believed at the time that these types of food didn't interfere much with blood glucose control.

Then Dr. David Jenkins, professor of nutrition at the University of Toronto, Canada, challenged the mental model about how our bodies absorbed simple carbohydrates and complex carbohydrates. As result of his work and that of others, we now have the glycemic index (GI). And for some simple and complex carbohydrates the GI recommendation is contrary to the previous thinking regarding "ok" foods for diabetics. (Some simple carbs are OK and some are not; some complex carbs are OK and some are not.)

Any human behind the curtain indeed holds "theories", hypotheses and assumptions. These are their mental models, which are a subset of their philosophies. Philosophies undergird everything. They undergird every discipline. They are simply a narrative about "what is real" and "what is success". **Behind every technology or practice is a human behind the curtain with a philosophy that shapes the space for your results: it limits and constrains what is possible to understand**.

Once we have an understanding of philosophies and mental models and have reflected on those that could help us, we begin to look at the data before us very differently. If we are wise about our assumptions or hypotheses, we'll always ask ourselves the question "what mental model might I be missing that is important to this system", and "what would I 'see' if I'm wrong?"

So where are these missing philosophies and mental models hiding? They are hiding:

- Inside of the question that you're asking – what problem are we solving?
- Within the decision made about what data to look at
- Behind the decisions about what features to extract from that data.

The Wizard of Oz is actually an ordinary man from Omaha, Nebraska. He lives with us. He's in our interpretations about our consumers, our payors, our physicians and he is us. We are the Man behind the Curtain.

The conversation between the Wizard and Dorothy's friends continued after the Wizard's confession:

> **Wizard**: "I'm afraid it's true, there is no other wizard except me."
>
> **Scarecrow**: "You're a humbug!"
>
> **Wizard**: "I'm afraid so..."
>
> **Dorothy**: "You're a very bad man!"

But we're not necessarily bad people. We're just missing an understanding of what it means to be human. This is a critical shift in thinking for our organizations. To have a bias is not 'bad'. It is human. It is unavoidable. Understanding that to have a mental model – biases, assumptions, beliefs, interpretations of how the world operates - is human, enables us to leverage the power of Big Data with humility.

THE TRANSPARENCY OF MENTAL MODELS IS CRITICAL FOR MARKETING

Marketers especially must make mental models transparent and bring them out into the open. Why is that?

1. Because our human capacity to learn from the data is located within the mental model that was used. When the mental model is invisible, we lose our reference point. We lose our ability or effectiveness to question and interpret the data when the mental model is not transparent.

2. The consequences of non-transparent mental models for marketers and their companies can be especially dire. Marketing has an essential role in a company's profitability. If their interpretations of market research are flawed and/or their marketing materials do not target or produce the audience that will buy a product, the company loses money and may eventually go out of business.

How do we “lure” mental models from their hiding places?

1. Seek to understand multiple perspectives (mental models) of causes and effects

   Charlie Munger, Warren Buffet’s partner, wrote:
   “Just as multiple factors shape almost every system, multiple models from a variety of disciplines applied with fluency, are needed to understand that system.” (Munger, 2005)

2. Keep them in existence for questioning: don’t lose visibility of your reference point.

Let’s say you’re about to launch a medical device or a pharmaceutical. There are numerous questions to answer, including:

- What are the physician views of the drug or device relative to other methods of managing the disease or condition?
- What are the unmet needs? How do they differ by stakeholder (consumer, physician, payor, or caregiver)?
- What are the current standards of care for the condition? Which audience is likely to encourage disruption of the existing standards of care or clinical protocols?
- What are the active and/or expected reimbursement policies for the conditions or disease? How will reimbursement for competitors or near competitors affect reimbursement for the drug or device?
- What is the “size of the prize” or market potential?
- What are the hurdles to adoption across the consumer, payor and physician?

Every person working on the launch has their own set of ‘mental models’. For instance, any number of people could speculate about a consumer’s response to marketing tactics from their own ‘mental models’ or perspectives:

An Economist ...

... might see the role of incentives –for the consumer, for the physician and for the payors – to drive product adoption.

A Literacy or Education Specialist...

... looking at the same marketing tactics might ask questions about the language used to describe incentives and how it might encourage inappropriate use, something an economist would likely overlook.

A Behavioral Psychologist ...

... might look at the psychology of perceived risk and how this might alter physician and patient behavior, regardless of the incentives. Yet the education specialist might not think about risk at all, never mind how it is explained. And the economist might not think about the effect of perceived risks on the ‘costs’ from the consumer’s standpoint.

A Sociologist ...

... might consider patients’ environments and the impact of living conditions on patients’ ability to take advantage of incentives. This objection could tie into that of the behavioral psychologist’s, but the educational specialist and the economist would likely never incorporate this perspective into their mental models.

Be sure you use multiple mental models and keep them visible!!

HOW MENTAL MODELS PRODUCE CONTEXT

Context is how people, places, or things (e.g., devices, drugs, perceptions of risk, incentives) are connected with the problem we're looking to solve or with the question whose answer we seek.

Once we formulate our problem, the question you ask is "What are the most important variables we must look for in the data?" The answer to this question is the context. Context includes the variables, "influences" or filters that will help us produce the most important information and connections for solving our problem.

John Muir was a Scottish-American naturalist. Interestingly, he was reported to have taken an 'unusual selection of courses.' [6] He wrote afterwards:

"When we try to pick out anything by itself, we find it hitched to everything else in the universe." (Muir, 1911)

Not only does data not speak for itself, but WE 'shape' and 'transform' it depending on the perspective (mental model) that we bring to bear on producing the context.

The mental model drives ...

> **....what context (e.g., sentiment)**
>
> **.... is derived from what sources of data (e.g., twitter feeds)**
>
> **... to solve the mental model of the problem (e.g., hurdles to adoption).**

As we saw when we attempted to anticipate consumer response to the use of incentives to promote a new drug, the response was 'connected' to the context produced by different mental models Incentives, perceived risk, language and environments are the context with which we select and examine the data for the drug launch.

Context doesn't 'appear' in Big Data. Context is produced by the mental models or perspectives we bring to the data.

In collaboration with Dr. Gregory Busse from the American University and Medical Content Strategist with Global Prairie, Accelerated Vision was looking to answer the question, "How do multiple FDA Twitter feed channels affect reach (the ability for FDA to reach its audience with its message)?"

A young computer science student was working with us to classify the twitter feeds using a particular data mining approach. He began to analyze the twitter feeds based on the account information and who was tweeting and retweeting. It did not occur to him to include the speed of response as a variable, nor the complexity of the content from a literacy standpoint. Other tools and approaches have to produce these contexts from the content.

For example, the time stamp (e.g., 9:00AM on Friday) from a twitter feed can't be used directly to indicate that someone is confused by the number of channels an organization is using to reach them. We may need to understand how much time elapsed between retweets.

[6] http://en.wikipedia.org/wiki/John_Muir

The twitter feed itself isn't putting up its hand and saying "umm... over here... the words I'm using are at a PhD level of complexity" or "umm... over here... they're at a grade 8 level of complexity".

Mental models – known or unknown – shape how data is interpreted. They:

- Impact the questions asked
- Shape the space for producing the context used to explore the data

BARRIERS TO LEARNING

One of the biggest barriers to learning is realizing that our mental models may be incomplete, or missing, or flawed. Learning is a feedback process. Single loop learning is what most of us engage in: we experience the real world, we get feedback about whether or not we achieved our objective, we act and we experience again. In other words, "we learn to reach our current goals in the context of our existing mental models" (Sterman, 2000)

This means improvement is restricted. We're driven by the gap in performance without questioning the model by which the performance was achieved in the first place. The effectiveness of a product launch and the related analytics are absolutely constrained by the mental models used. Are they visible? Are the teams aware of what they are? Are they reaching out and examining what might be missing? Did the analytics team produce the most powerful context?

To improve our productivity in this new global era by driving down errors and increasing insights, we must now compete with our mental models, not just with our products.

CONCLUSION

So, how do you use Big Data to gain insights into answering the questions you care about? You make and keep visible as many mental models or perspectives as are relevant and valuable for solving your problem in order to produce the context necessary to collect, cull and interpret the data.

Appreciating the role of context requires us to acknowledge:

1. Context doesn't appear in Big (or Little) Data. **Context is produced.**
2. Context is produced by the ever present mental models and perspectives that we bring to data.

With this knowledge, you can now begin to observe in your healthcare or life science organization the assumptions that need to change before "Big Data" can be a reliable source of power capable of delivering competitive advantage to your organization.

When examining the "outcomes" from Big Data, what do you need to understand? The critical understanding is that you must acknowledge and pay attention to the Man behind the Curtain! It is critical to acknowledge the mental models of various consumer cohorts, physicians, payors, and most importantly your own mental models when producing context. And, despite what we have heard, data does not speak for itself. Context is produced from mental models. Invisibility, denial, or ignorance of these models means we go through life "... like a one-legged man in an ass-kicking contest..." (Munger, 2005).

To leverage Big Data into the marketing and operational insights capable of accelerating your organization's or a brand's position in the marketplace, you must account for the mental models capable of influencing your interpretation of the data analysis. And, given that healthcare includes an array of consumer, caregiver, physician, and payor stakeholders, your organization and brand leaders – and quite often the analyst these leaders trust with their performance – must inventory and account for the mental models operating within and across each stakeholder audience, and their resulting contexts.

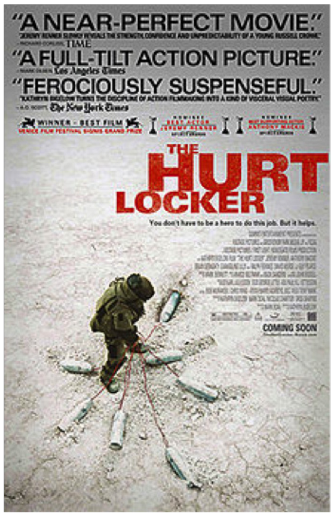
If this seems complex, it is. This is because you are working within a number of complex systems. Brand optimization happens in a context. Point of Care influencers are operating in a context. Our Consumers' knowledge, attitudes and behaviors are operating in a socio-ecological context of families, communities, policies, etc. These are called 'complex systems'.

The goal, however, is to deliver the actionable insight that clearly defines the strategic and tactical execution required to succeed within and across healthcare's diverse set of stakeholders. And you can reach this objective more easily than you think if you work with people who understand how to collect, cull and interpret the data from complex systems.

In the next white paper we explain more about how to work with the data gleaned from complex systems.

For example, the benefit of accepting and understanding complex systems is the ability to identify the contexts that are the "leverage points" within a system of mental models. A leverage point is a place in the system where a relatively small amount of change results in a large change in system behavior. These are important points or contexts to observe in complex systems because they keep costs low for producing a large effect.

In the movie The Hurt Locker, the hero, a bomb disposal expert, is tracing a wire. He arrives at a point where multiple wires are connected ... to multiple bombs. The point of connection is the leverage point, where tripping one single wire will cause a much bigger explosion than anticipated from a single wire connected to a single bomb. Creating the leverage point was lower cost for the bomb assembler than assembling seven separate bombs, and, of course, a much higher cost for the man or crew dismantling the bombs, not to mention the cost if the bombs had gone off.



In the healthcare world obesity is a leverage point because lowering weight is a low-cost way to dramatically affect so many of the operations of the complex system, such as those of the pancreas (diabetes), heart (cardiovascular problems) and behavior (self-esteem).

We'll talk more in the next whitepaper about how marketing teams can use these "leverage points" and other features of complex systems to more effectively interpret their data and produce competitive advantage.

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GLOSSARY OF TERMS

Complex System:
A complex system is an organization of structures (e.g., entities like people, equipment) that are interrelated and characterized by 'feedback mechanisms': positive feedback (reinforcing mechanisms) and negative feedback (self-correcting or dampening mechanisms). A complex system has specific characteristics:

- Intractability: feedback loops create a life of their own so complex systems are hard to manage – such as the economy.
- Emergence: properties of the system that emerge that are distinct or novel from the properties of the individual parts (e.g., such as a personality)
- Incompressibility: the best representation of a complex system is the system itself. For instance, it's difficult to subdivide a person.
- Quasi-Reducibility: while complex systems are incompressible they may be quasi-reducible – the ability to articulate some aspects of behavior by eliminating certain parts.
- Evolution: complex systems evolve over time and the changes are structural or permanent making it impossible to go back.

Context:
How people, places, or things (e.g., devices, drugs, perceptions of risk, incentives) are connected with the problem we're looking to solve or with the question whose answer we seek.

Leverage Point:
A place in the system where a relatively small amount of change results in a large change in system behavior.

Mental Model:
A construct and a collection of typologies for categorizing experience (Sterman, 2000), or a framework for gathering, processing and acting on information (Munger, 2005)

A set of assumptions about a system -- its purposes, the relationships between components in that system, and how it operates

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