4 Success Rules for exploring key success drivers out of data

Why is a product bought by senior customers more attractive to young people? Why might a factor that is useless in predictive analytics be your most important reason for success? Why might providing some product samples be beneficial but their extensive use can harm sales? We will now explore the hidden side of business facts. Together we will venture in a world were you can see the **reasons behind facts**.

In this a paper, business leaders can learn how to pinpoint the real factors that are driving business success through smarter, savvier analytics, technology use and marketing.

Summary: 4 Questions You Should Ask your Analytics Vendor

Today's business intelligence tools and market research reports produce transparency **but no answers to "why" questions.**

It is an **imperative to understand indirect relations between factors**. This is one of the reasons why one should not solely rely on predictive analytics when it comes to find answers to "why" questions.

Finally, what we need are methods that help us to **explore** nonlinear relations and **complex interactions without assuming things you don't know.**

So, if you're assessing customer insight agencies or software packages in your quest of making sense of data and your complex business, we recommend to **ask the following questions**:

1. Are you using multivariate methods to prevent spurious findings?
2. Are you using a path analytics approach to capture indirect and direct effects?
3. Are you able to uncover nonlinearities and interactions – those kind where you don't know that they exist?
4. Are you able to capture a wide net of factors in order to explore important factors you don't know of upfront?

And now read why all those analytic features will help you boost usefulness of your insights:

Why Do You Urgently Need to Escape the Data Fallacy?

A new way of thinking has taken the management and marketing establishment by storm in the past decades. The idea that decisions should be based on facts – not just on manager's opinions or experts judgment. Business intelligence and evidence-based management became not just established buzzwords but service industries. The advent of unlimited data feeds by the internet and social media started a new wave of data enthusiasm – **Big Data**.

How a badly voted product design can turn out to be a sales booster

Recently I got a call from a major brewery. The management wanted to launch a new label and case design and was wondering whether the new design would foster sales. So far, a standard request. What market researchers do in those cases is testing the design concepts by asking target customers: "Will you buy this case of beer?" If the new case attracts few "yes" answers and subsequent buyers, it's a failed design. Correct?

Wrong! The result of our analysis was that while the new design scored slightly lower with respect of buying intentions, it was in fact more appealing to customers, and it has been associated with properties that drive sales. Still the new design felt somehow "unknown" – it lacked familiarity. Exactly this turned out to be a second reason for buying the product. – in this case a reason for not buying the new design.

Familiarity usually grows automatically over time. That's why it can be expected that over time the new case will substantially increase sales, although market research didn't show it. **Should we really decide on facts?**

Why is a product bought by senior customers more attractive to young people?

Recently I found myself sitting in a kickoff meeting. A meeting in which a company was trying to stop declining sales. As it turned out, a major reason for this unfortunate situation was the management's own reliance of "facts".

This lottery enterprise instructed me that their target customers are older than 40 years and winning the "jackpot" is their main reason to buy lottery tickets. The reason for this conclusion was the consistent observation that a majority of customers were seniors and that sales exploded every time a jackpot increased in value. Based on these insights the management adjusted their marketing material and strategy. It seemed to be a reasonable strategy that ads were mainly promoting jackpots.

We studied the true reasons for customers to buy lottery tickets and were astonished about the simplicity of an alternative explanation for the "facts": What drives sales is a ritualized playing behavior and the experience of winning in general (not just jackpots). Both factors grow over time, which is why seniors are more common among customers. However, we also found that younger people are actually more likely to buy lottery tickets - given that they had no lottery experience so far.

By focusing on jackpots in ads, the company discouraged ritualized playing behavior, and by targeting seniors, the company missed out to win new customers with a long-term attachment to the company's product**.** So, I am asking: "**should we really decide on facts?".** Sure we should, but facts can be more complicated as it seems.

Why do customers who pay higher prices may have a low willingness-to-pay

It was a rainy November day several years ago that ended with a great "Aha" moment. I was a sales and marketing director at that time and sat together with my sales reps to review the team's monthly performance. I checked our Business Intelligence (BI) tool and asked some questions:

"Why did our sales in that product category decline?" is a typical question. The answer from one of my team was immediate. "Oh, because a particular customer's demand has declined". But after this answer I realized that I just had selected the wrong timeframe and sales actually increased: "Sorry my fault. So, why did our sales increase so much?". Likewise, the answer was immediate: "I was successful in cross-selling with customer Y" my team member responded. Ok. Obviously any fact will find explanations.

After this amusing experience we sat down and used our BI tool more systematically in order to identify potential target market segments for the whole team. We found that companies producing pharmaceuticals were paying much higher than average prices. "Oh great. Let's target those companies". Our sales reps immediately became active and contacted the promising companies. Unfortunately, with little to no success. Why?

My own methods from my days as a PhD student brought something more meaningful to light. Those pharmaceutical companies did not pay a penny more compared to average customers. They simply ordered smaller than average volumes and thus received higher priced proposals. **Should we really decide on "facts"?**

Many managers have had such experiences but many draw the wrong conclusion. They simply try to dig deeper into data. May the "facts" that result from such actions be misleading because they are too aggregate? The answer is "typically no". The reason is that outcomes are simultaneously influenced by many factors. Disaggregation cannot separate their effects. **It remains a dead end**.

Instead, what we need to know is what causes our success measure to change. And **correlation simply does not tell us anything about causation.** In markets there are always dozens of factors that simultaneously influence success. In order to find out the contribution of a single potential success driver, you need to consider and model all other success factors. Looking at just two rows of data is a dead end – no matter if it is "age", "design" or "customer industry" vs. "likelihood to buy" or vs. "accepted price".

„There is nothing more **deceptive** than an **obvious** fact"
(Sherlock Holmes)

Comparing facts and interpreting other correlation is very dangerous, because in many cases it leads to **wrong decisions**.

Why Predictive Analytics don't Tell you Anything about Success Drivers?

The quest for "what"-questions and the search for hidden reasons for success has brought early researcher to a sobering insight. **It is useless to correlate** potential success drivers with measures of success. It is **meaningless to compare** properties of those who are successful with those who aren't. This approach simply does not consider the impact of other factors and inevitably must erroneously ignore the influence of other factors.

This was the rationale behind the invention of regression techniques which are foundational of most predictive approaches. Regardless of whether regression techniques come in the disguise of "econometric modeling" or "artificial neural nets", they do what is required to find factors that drive success in the context of all other factors that have an impact: **Great, mission accomplished, correct?**

Why marketing-mix models can fool you

One day, I presented Andreas the results of his TV spend on sales using predictive techniques. He nearly fell off his chair. There was almost no effect. "I need to dump the whole TV budget immediately" he screamed at me. The results were correct and wrong at the same time. Why? It was correct because, this is what the data said, based on mathematically accurate processing, and the results that a top-notch marketing-mix agency would have produced. **It was wrong because these were just results from predictive techniques.** Those just model the direct effect of a particular factor on an outcome.

Predictive techniques do not consider that **TV spending does not just leverage sales directly**. TV spending makes people google and click on search advertisements, it makes target customers call the call-center, visit the company's website or online shop. Those resulting actions have positive consequences, too. One could argue that all those action items should also be included in the model as predictive factors to guarantee meaningful results. As a consequence the coefficients of a predictive models would tell you what the impact of TV spend is **when viewers do not google,** click on ads, call the hotline, and visit the website or the shop. But this is not what Andreas would like to know. It is exactly the indirect effects among predictive factors which tell a different story. Knowing this we were able to help Andreas by separating the indirect from direct effects of his TV spendings on total impact ROI measures.

"If you have a hammer, every problem looks like a nail." Even though most statisticians know that factors in predictive models are assumed to be independent, they tend to forget it since it is the hammer everyone uses. If you do not believe me, please visit the websites of leading providers of predictive analytic suites. **They promise to quantify the impact of success drivers, but they don't.** This is what I call "The Predictive Analytics Fallacy".

Why can you compete in some price-sensitive markets without price related moves

I was sitting in my favorite chair with a smile on my face. It was Jack on the phone: "Our new market initiative has an overwhelming success. However, I don't know why". This was new to me. Typically customers contact us when something went wrong. We took the brand tracker data of this service provider and took a **deeper look into this "why" question**.

To me it is like sitting as a child in front of a puppet show and the curtain opens: the moment when our algorithms spit out the results. What we found was astonishing but largely useful. The new price scheme that was launched in the service provider's initiative was not directly driving brand consideration. In other words, **conventional driver models would erroneously have told us that price has no impact at all.**

It was just feeding the story of being "the challenger" against the market leader, which itself was a major reason why new customers were attracted by the brand. This led to a highly profitable recommendation: To keep momentum –you do not need to continue lowering prices. Instead introduce other initiatives that feed the "the challenger" story.

Predictive analytics is a great discipline. It is good in making predictions, but it largely fails **in providing insights regarding "why" questions.** You need to dig deeper, much deeper.

"If your only tool is a **hammer**,
every problem looks like a **nail**."
(Abraham Maslow)

Predictive Analytics does predictions.
What it does **not** do is telling you
what **causes** success or failure.

Why your world in business analytics is not flat

If you spot a red rose, smell on it and walk with your eyes over the details of its blossom, you will discover amazingly complex forms, colors, smells and surfaces. Although a red rose is highly complex, it is just beautiful. When we look at the picture of how things relate to each other, we rather prefer lines and squares. After 20 years data mining experience I can assure you: **business reality does not consist of lines and squares at all.** Instead it has great complexity and with it comes beauty.

Why spreading a few product samples may work and a lot don't

Daniel was leading the commercial effectiveness department of a pharmaceutical corporation. His educational background as a molecular biology expert has made him skeptical about conventional modeling techniques that were promising to **measure the ROI of his marketing and sales activities.** "A houseplant has two success factors,

water and sun" he said to me "if you put the plant in the dark basement, you can pour as much water as you like, without any positive impact".

This is what conventional techniques neglect, they assume factors to be independent. If they don't they assume something else. They assume lines or squares where reality holds beautiful curves. And this was why Daniel was calling me.

We collected the best sales and marketing data available. Beside sponsorships, local workshops, journal advertisement, brand reminder, direct marketing material, there was also the instrument of providing product samples. Conventional models would have indicated "yes, **product samples works, the more the better**".

What we found looked beautifully complex and interesting, but odd at first sight. The relation had an inverted-u shape. At some point, providing sample did more harm than good. How can this be? Surely, every peace you provide to physicians will be handed over to patients. But physicians typically have limited patients. **Too many samples do not stimulate but substitute prescriptions.** That is how simple, plausible and beautiful real word complexity can be.

Why rebates sometimes work and sometimes don't

Recently, we dove into modeling success factors of sales in apparel stores. Two factors, "tangible rewards" and "good interpersonal communication", seemed to be of major importance as standard multivariate models indicated. Conventional methods suggested "do both, the more the better". What we found using advanced methods was much more beautiful, complex and meaningful. It turned out that tangible rewards **only show impact if interpersonal communication is weak.**

Reversely, improving interpersonal communication would already bring the highest return even when no tangible rewards were given to customers. Research in motivational psychology knows this phenomenon: **extrinsic motivators like tangible rewards and intrinsic motivators does not add up**, it can just substitute each other.

The recommendation to business is highly profitable: We found that training and choosing right staff is the lower investment compared to giving tangible rewards to customers at the long run. Indirect price discounts were prevented, sales margin grew by 2 percent bottom line.

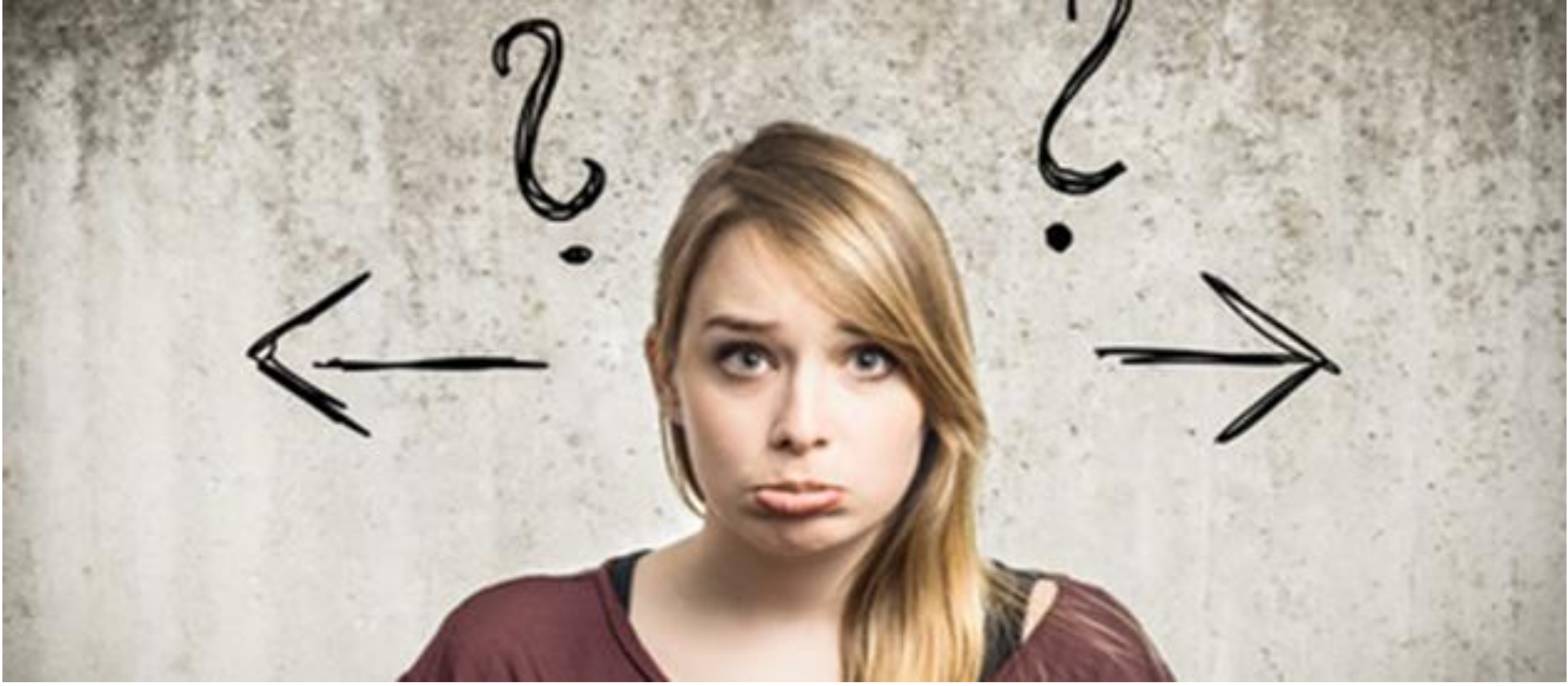
When I present such examples to statisticians and other experts in quantitative reasoning they tend to say: “I can do the same with standard procedures”. What they usually do not consider is the fact that standard techniques can only model complexity (i.e. interactions and non-linearity), if the type and form of complexity is known upfront. **But this is typically not the case in practice.** For instance, you need to know upfront that intrinsic and extrinsic motivators does not behave like water and sun for a houseplant (“AND” interaction) but is characterized by an “OR” interaction. In cases with 50 factors you then need to specify more than 2500 combinations and its types. What practitioner need in order to learn from data are methods that help to explore something new, something unexpected.

Fred Bookstein ones said at a scientific conference “A research method is valuable when it has the capacity to surprise with **findings that hits you like a rake between your eyes**”. This is exactly what I experience week by week.

Recently we were researching the top buying factor for a B2B production company. We asked the industry experts about the buying factors. However, as a kind of non-expert in this area, we felt uncomfortable with the list and added a few more items that are known from the literature. Then we studied which hidden factors truly drive decisions. Amazingly, **two of the resulting top three drivers were not on the expert**

"The pure and simple **truth**
is rarely pure and **never** simple.”
(Oskar Wild)

Valuable analytical methods do not just test hypothesis.
They have the capacity to **explore unexpected** insights
– no matter if they are nonlinear or moderated.



list. The business world is too complex, too beautiful, to purely rely on simple judgments.

We need to acknowledge that the world is complex like a beautiful blossom. Conventional statistics take a reductionist approach. They force data to be linear and simple and usually do not account for the data's inherent complexity. **Explore non-linearity's and complex interactions without assuming things you don't know.** The insights will hit you like a rake between your eyes.

4 Questions You Should Ask your Analytics Vendor

The greatest fallacy of the **ever growing data euphoria** is that raw facts tell you anything on what's important. No matter how you aggregate or disaggregate data you will not be able to find what is most valuable to drive your business. **Today's business intelligence tools and market research reports produce transparency but no answers to "why" questions. .**

Multivariate statistics were designed to help, but by just grabbing in the toolbox of conventional statistics you're close to tap in the next trap. Most prominently, it is an **imperative to understand indirect relations between factors**. This is one of the reasons why one should not solely rely on predictive analytics when it comes to find answers to "why" questions.

Finally, standard statistical methods force users to make assumption that often does not match with reality. What we need are methods that help us to explore nonlinear relations and **complex interactions without assuming things you don't know.**

So, if you're assessing customer insight agencies or software packages in your quest of making sense of data and your complex business, we recommend to **ask the following questions**:

5. Are you using multivariate methods to prevent spurious findings?

6. Are you using a path analytics approach to capture indirect and direct effects?

7. Are you able to uncover nonlinearities and interactions – those kind where you don't know that they exist?

8. Are you able to capture a wide net of factors in order to explore important factors you don't know of upfront?

With asking these questions, you are more likely to make sense of all this Freakometrics out there. I can promise - this venture will be truly exciting. The beautiful part is that complex modeling of unknown properties will often quickly transform in something very simple. You will find those 20% simple but powerful insights that explain 80% of your success. That is how complex beauty transforms into simple actionable results.

"The **price of light** is less than the cost of darkness."
(Arthur C. Nielsen)

Powerful methods for **uncovering** drivers of success need to be multivariate, consider indirect paths, model unexpected nonlinearities and interactions.

About Author: Frank Buckler, PhD. is a distinguished expert in uncovering management success drivers. He is the inventor of the "causal analytics" platform NEUSREL that eliminated the drawbacks of conventional methods in order to meet the requirements of business applications. Frank has eight years' experience as a marketing & sales director and is bestselling book author, publishes in magazines and, and speaks regularly at leading industry conventions.

Neusrel Causal Analytics is specialized in answering one single question of its clients: "what drives market success". Out of its US office in Santa Barbara, CA it serves leading brands such as T-Mobile, SONOS, L'Oreal, AUDI or Deutsche Bank.

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Experts about NEUSREL

„I am intrigued by the non-linear/interaction capabilities“

Claes Fornell (a leading PLS pioneer),
Professor of Marketing, University of Michigan

„This innovation reinvents success driver research.“

Torsten Hennig-Thurau, (Top 1% scholar),
Professor of Marketing, University of Muenster

„Incredible. You're inventing a whole new methodology."

Edward E. Rigdon (initiator of SEMNET) ,
Professor of Marketing, Georgia State University

Customers about us

We learned that we are sitting on data which are a goldmine of insights. NEUSREL is the only institute I know of that is equipped with the right expertise and methodology to help us explore such useful insights.

Marc Güntermann, Head of Service Development After Sales, Ph.D., AUDI AG

NEUSREL helped us to focus our communication on few key elements. …I was impressed how the team delivered …reliable, easily understandable results … _

Christiane Mougey, Managing Director
SkinCeuticals,
L'OREAL

NEUSREL provided us the confidence to advise our business partners on the most effective and efficient means for sustaining our brand momentum.

David Feick, Ph.D. Director Consumer Insights,
T-Mobile USA