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THE 5 PILLARS OF DATA SUCCESS: A SKILLS-BASED TEAM APPROACH TO DATA-DRIVEN MARKETING

There is a well-known conundrum in marketing analytics: Although companies are investing billions of dollars into ever-evolving data-driven approaches, their (perceived) contribution to companies' overall performance remains low. In fact, the gap between access to data and the ability to develop actionable insights is increasing. In this theoretical paper, I explore two potential contributing factors to this development and propose a skills-based team approach designed to help marketing analytics deliver the value it is already creating - but often can't realize.

The Triumph of Data

Hardly any topic has created more buzz in recent years than the strategic use of data. Terms like data science, artificial intelligence and marketing analytics are top of mind for both agencies and their clients. The hype surrounding the world's new "most valuable resource" (Parkins, 2017) also shows in Google's search trends. For example, the term "artificial intelligence" now has a significantly higher search volume than Britney Spears --- who was for the longest part of the 2000s (seven out of ten years) the person with the highest search volume worldwide; even ahead of Harry Potter (Google, 2018). According to Google, interest in artificial intelligence increased more than fivefold between 2013 and 2018 (see Fig. 1).

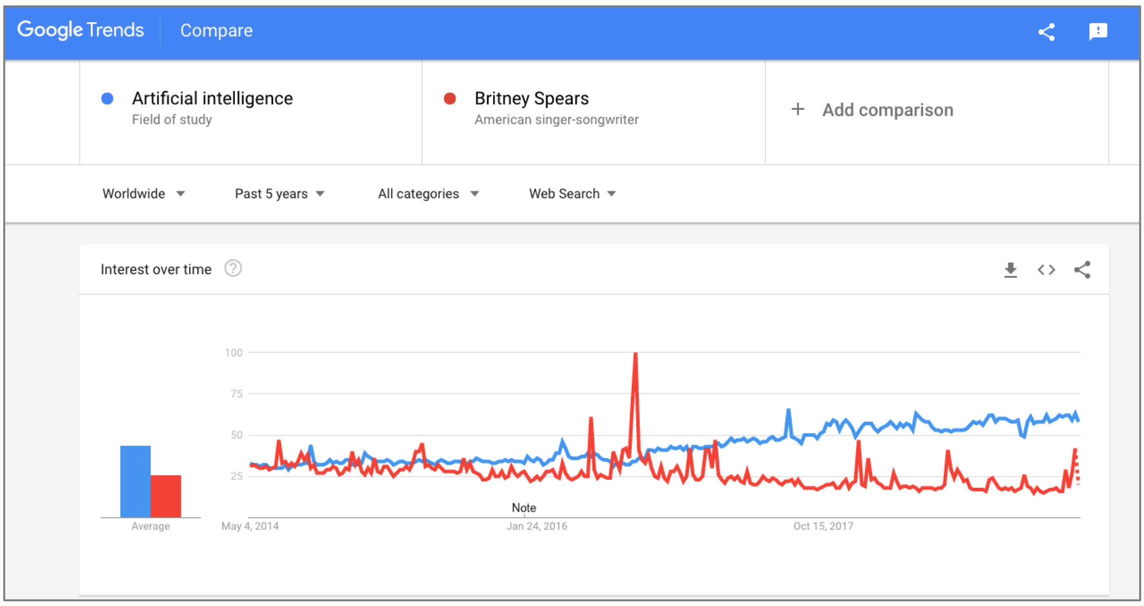

Figure 1: Google Search Graph. Source: Google Trends

But not only the search behavior of the general Internet population reflects the increased interest in data within marketing. According to the "CMO Survey" conducted by Deloitte, Duke University and the American Marketing Association (AMA), leading marketing executives have been forecasting a constant increase in spending on marketing analytics for some time now. According to these estimates, companies could soon be spending a quarter of their entire marketing budget on analyzing the data available to them --- or on acquiring and utilizing new data (Deloitte, 2017). Even today, companies are investing billions into data-driven initiatives (Berinato, 2018), often in the hope of innovative marketing approaches.

The Problem with Uncertainty

But why do companies choose to diverge an increasing amount of money away from concrete marketing activations into data analytics? Which factors --- in addition to increased technical capabilities and the decreasing cost of data collection and processing --- motivate companies to set aside larger budgets for the aggregation and analysis of data?

One key factor is uncertainty. Uncertainty as to whether ever-increasing business goals can be met with often decreasing budgets. Many marketers feel that the technology-fueled increase in marketing efficiency has reached its natural cap and that continuous exponential growth in many areas is unrealistic (and that focusing exclusively on conversion is unhealthy for a brand). Nevertheless, many companies are forced to achieve more with less. Resources must be invested efficiently; the performance of marketing campaigns and product innovations constantly monitored and, if necessary, optimized in (near) real time.

The problem with uncertainty in this scenario is that it creates stress among marketing managers. Avoiding this type of stress by reducing uncertainty and increasing predictability is a fundamental human need (Berger & Calabrese, 1975). While this is usually done by employing specific communication tactics (e.g. questioning layers, disclosure), companies often bank on data to provide clear predictions and "guaranteed success" in marketing initiatives. One result of uncertainty reduction is an increased focus on Return on Marketing Investment (Fig. 2) and the urge to implement data-driven marketing.

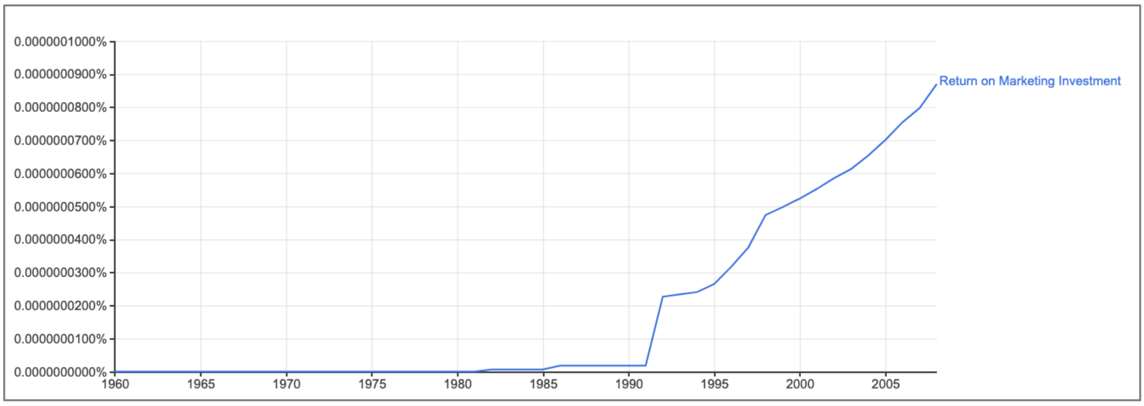

Figure 2: -Increased interest in Return on Marketing Investment. Source: Google nGram Viewer.

The Unpleasant Truth

The truth, however, is: data alone are not enough. The mere existence of data in companies is no guarantee for increased Return on Marketing Investment. On the contrary. Despite further increases in the funding for data-driven marketing in recent years, the majority of marketing managers in Deloitte's "CMO Survey" stated that "Data & Analytics" had not yet made a significant contribution to the overall success of their companies (Deloitte 2018). What's more, the gap between the availability of data and the ability to translate them into actionable insights has doubled in recent years. While in 2012 about 14 percent of surveyed companies stated that they generate sufficient data but cannot use them profitably, the figure had risen to 28 percent in 2017 (Ransbotham & Kiron 2018). In other words: Although companies spend more money and have an increasing amount of data at their disposal, relatively little actionable knowledge is derived from them.

One possible reason for this discrepancy lies in the fact that organizations --- under increasing pressure to implement data-based methods (LaValle, Lesser, Shockley, Hopkins, &

Kruschwitz 2011) --- often rely on one of two easy-to-implement but rarely sustainable strategies: the “jack of all trades”-analyst or building a pin factory.

- In the *“jack of all trades”-scenario*, a data-savvy employee with a (computer) science background is hired and then supposed to transform the entire marketing process by himself, often isolated from other divisions within the company. This approach can be traced back to Davenport and Patil’s (2012) declaration of data science becoming “the sexiest job of the 21st century”. Their much-cited article described data scientists as a "hybrid of data hacker, analyst, communicator, and trusted adviser" (p. 73). Ignoring the fact that not all computer scientists fall under Davenport and Patil’s definition of a data scientist (their article actually warned that the ideal combination of skills remains rare), many marketing departments were convinced that hiring a single computer scientist would be sufficient to establish advanced analysis processes throughout the entire company. Given the continued shortage of data science talent (Ransbotham, Kiron & Prentice 2015), this solution was (and is) tempting. However, the problem is that a single person isolated from the rest of the organization can't possibly solve the expanding range of problems companies are trying to address using analytics. Many of them require in-depth knowledge of an organization's underlying structures that go far beyond the boundaries of traditional marketing or business intelligence. How widespread this practice is, however, is shown by a study in which only 20% of the companies surveyed were rated as "analytically mature" due to their combining of data from different business areas when gaining insights (Ransbotham & Kiron 2018).
- In a *pin factory*, labor is strictly divided. Instead of hiring a “jack of all trades”-analyst, each division (either within the marketing department or the company as a whole) employs its very own specialist. Even within a single marketing department or agency, essential data functions are often carried out by individual

specialists within different units: market research within the strategy unit, web data within the digital unit, marketing mix data within the media unit, and so on. Specialists' work is then coordinated by a manager, with hand-offs between the functions in a manner resembling the pin factory (Colson 2019). This problem even gets amplified as soon as additional departments or agencies are involved. Although individual data workers might allow companies to analyze more data and potentially achieve incremental improvements in individual areas of the business, wide-ranging data-driven innovation remains unlikely. The division of labor --- and the highly skilled narrow task specialists it affords --- has led to enormous increases in efficiency in many industries, but marketing analytics cannot be organized this way for two reasons: Firstly, as described in the "jack of all trades"-scenario, company-wide analytics-driven innovation requires the integration of data from different areas of the business. And this is difficult to achieve. Even if data is shared beyond the boundaries of a particular department, a considerable amount of information might be lost during hand-off. In addition, the "receiving" departments often lack the necessary expertise to correctly interpret the data. If, for example, the sales and marketing departments analyze the results of their respective initiatives independently, they might not take into account confounding factors created by or at least known to the other side. They might attribute recent success to their initiative even though it was actually created by environmental factors. In isolation, for example, the separate and combined effects of a marketing campaign and the simultaneously introduced sales incentive on the can only be insufficiently be analyzed when looked at separately. The second argument against unit-specific analytics functions is that --- in contrast to an actual pin factory --- the exact specifications of the "final product" are often unknown in marketing analytics. Division of labor can only function if all requirements can be precisely defined before the start and the project and therefore be divided into clearly defined tasks. The textbook example is Smith's (1776) pin factory, where the demands for every worker are clear and the only goal is to execute the specified steps as efficiently as possible. Data-driven marketing, on the other hand, is explorative by nature. The development of new capabilities requires flexibility and agility; solutions must be tried out in practice, often adapted in the middle of the process, and therefore cannot be planned in advance (Colson 2019).

The Five Pillars

If a successful analytics culture cannot be based on these popular approaches, how should it be structured? In order to answer this question, one needs to understand that implementing a data-driven culture is both a talent and a management challenge. Hiring individual employees, whether as jacks of all trades or workers in a pin factory, is insufficient. Without a company-wide, top-level "buy-in", data-driven approaches often falter even though they show initial promise. A lack of managerial support remains one of the top reasons for failed data-based initiatives within companies (Berinato 2018; Schrage & Kiron 2018).

The second challenge is to identify the required talent and connect it. This is where the "Five Pillars" come into play. They consist of five core competencies that can serve as the basis for successful data-based marketing. Although a competence-based approach is far from new (e.g. Drew Conway's "Data Science Venn Diagram"), but in contrast to previous approaches, the five pillars don’t focus on combining as many competencies as possible in one person, but rather on bringing together different people from all over the organization in one integrated, agile project team. This team is inherently dynamic and can be assembled as needed with the best qualified people for each task. This not only ensures that the relevant expertise is available, but also that data-driven approaches are less likely to be perceived as an external initiative - a factor that often hinders acceptance of such solutions.

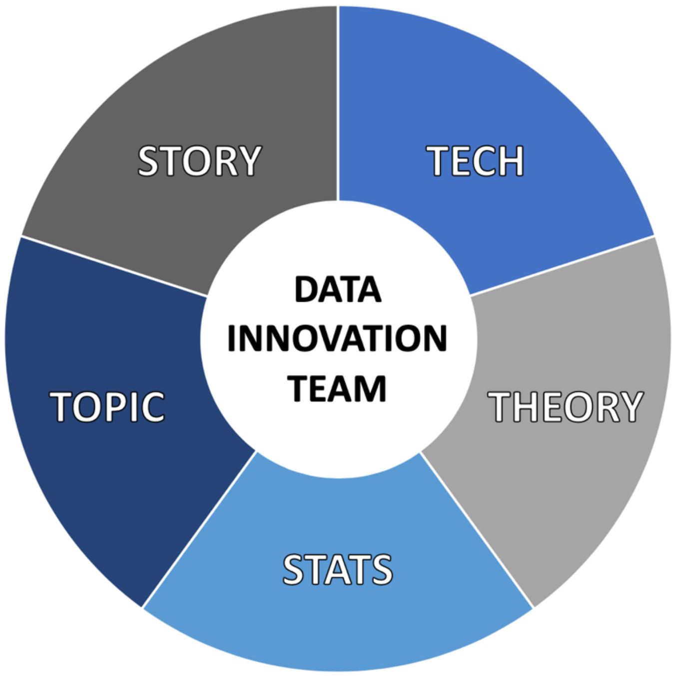

Figure 3: The five competencies of data success

<u>In the following section, the five competencies are briefly presented:</u>

1.) Technical expertise. When companies talk about establishing an analytics function, they often have a very specific profile in mind: a person with a computer science degree and substantial knowledge of programming, databases and digital technologies. This is indeed often the foundation of any data-driven marketing, as a large portion of the data accumulated in companies now lives in the digital space. In addition to real-time online tools such as Google Analytics, Chartbeat and Salesforce, information sources that have traditionally been slow to update --- such as brand tracking or customer and market research --- now also deliver a steady stream of digital output. As a result, organizations are collecting more data than ever and many (marketing) departments are suffering from information overload (Meyer, 1998). The greatest contribution that technical expertise can make to data-driven marketing is therefore usually not tapping new data streams, but rather their aggregation and integration across departmental boundaries (Schrage & Kiron 2018). A consolidated database not only forms the single source of truth for all further analysis steps and reduces the number of individual reports, but also helps to break up silos in companies. Breaking down these silos in turn makes it possible to identify previously hidden relationships between variables that are located in related but traditionally separate areas of the company. The combination of leading indicators (e.g. web statistics available in real time) and lagging indicators (e.g. brand metrics reported on a quarterly basis) is particularly valuable. Enabling this proximal interdisciplinarity (Yegros-Yegros, Rafols, D'Este 2015) opens up the greatest opportunities (Ransbotham & Kiron 2018). Technical expertise is traditionally found in business intelligence departments or IT - but it can slumber everywhere.

Theoretical Expertise. Data itself hold no power. Their power derives from their ability to answer questions. Consequently, the usefulness of data depends as much on the quality of the data itself as on the quality of the questions being asked. Raw data must be transformed into information - which means it must be endowed with meaning and purpose (Drucker 1988). This usually requires knowledge of social sciences and communication theory, which is rarely associated with computer scientists (Berinato 2018). Questions about human behavior call for a social-scientific competence spectrum that allows a broad view of macro trends and thus enables the development of testable hypotheses based on sound theoretical knowledge. This is essential, since big data pose another major problem: the bigger the dataset, the easier it is to find statistically significant relationships – even if such relationships make absolutely no sense. For example, what does the consumption of beef in the United States have to do with new car sales? Statistically speaking: quite a lot. Between 2000 and 2009, the two values moved almost uniformly --- creating an almost perfect correlation of .94 (see Fig. 4). Such strong positive linear correlations are rarely found in academic experiments. This, of course, is an extreme example, whose obvious absurdity affords no social science degree to debunk. No sane person in automotive marketing would try to stimulate beef consumption in hopes of benefitting the automotive sector. Nevertheless, there are many situations where a sound knowledge of basic (social) psychological processes and human computer interaction is needed to facilitate informed hypothesis-writing and thus increase the potential usefulness of data within marketing department. Theoretical expertise is traditionally found in market research or marketing communications units.

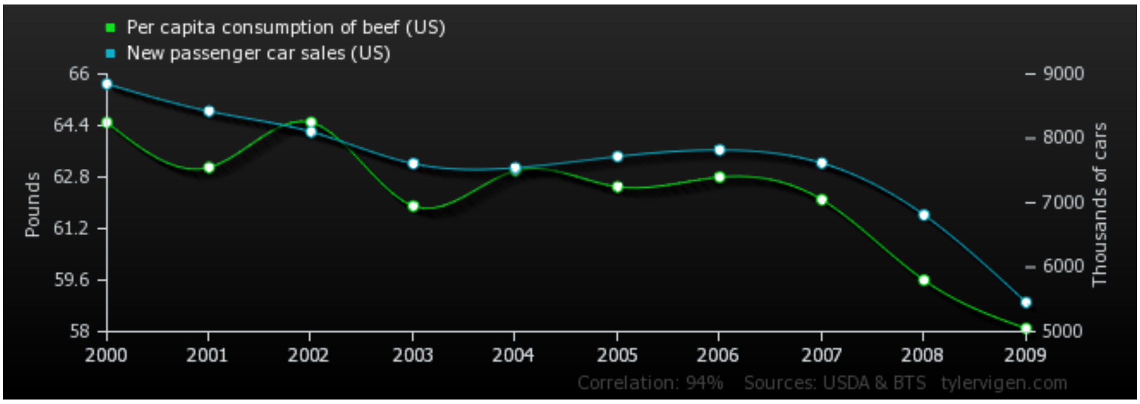

Figure 4: BEEF & CARS. Source: Spurious Correlations; tylergiven.com

3.) Statistical Expertise. Once hypotheses have been set, they must be rigorously tested. Many companies rely on the technology-savvy employees, who are already responsible for aggregating and integrating data, to also compute statistics. In many cases, these "data wranglers" do have the skills to run statistics, but just because a certain degree of technical understanding is a necessary prerequisite for calculating statistics in many data environments, it is not sufficient. Technical expertise is not synonymous with statistical competence, nor does it guarantee that data will be transformed into information accessible to non-scientists (Berinato 2018). It is certainly possible that employees with a computer science background also have a broader statistical understanding. However, detailed knowledge statistical significance, power analysis, and the assumptions underlying different statistical techniques as well as their interpretation is usually not part of their core competence. Indeed, the ability to calculate meaningful statistics has been identified as a separate --- and one of the most important --- competencies in analytically mature organizations (Ransbotham & Kiron 2018). This knowledge often comes from the academic environment and can be found in different areas of the company, such as sales planning.

4.) Subject Matter Expertise. The ability to translate statistical significance into meaningful insights is largely based on the ability to associate general consumer behavior with a specific business context. Therefore, expertise and subject knowledge will be crucial in two main areas: 1) in specifying general business hypotheses; and 2) in translating the analysis results into relevant insights that are consistent with both business strategy and organizational processes (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz 2011). Data-driven marketing can only flourish if the findings are aligned with the general business challenges of a company. Although the ability to apply overarching social science theories provides a solid foundation for deriving hypotheses, they are far too general without company-specific refinement. The resulting strategies would be very generic (e.g. for an entire industry) and would only give a single company a short-term advantage as competitors can simply copy the resulting initiatives. In fact, there are several variables that can only be identified if stakeholders are aware of the peculiarities of the enterprise to which the data are applied. For example, when examining why some teams in the National Basketball Association (NBA) generate more fan interactions in social media, it is important to know the sport of basketball, its fans in general, as well as and the structure of the NBA and its individual teams in particular. Factors such as the reach of different media outlets in the respective markets, the television presence and success of the respective teams, the popularity of individual players within the teams, the support of the league, as well as the content and organizational structure of the teams all affect fan engagement at different levels. Only when a general question is enriched with company-specific details can an analytics framework unfold its full potential. This specialist knowledge is usually found in companies at product or strategic level or is available externally via agencies and associations.

Storytelling Expertise. The best marketing analytics strategy is useless if its results are never implemented. The so-called last mile problem, the inability to communicate results in a language that executives understand, has been known for more than 100 years. And yet, these internal and cultural barriers are still identified as the biggest obstacles to fully implementing data-driven innovation in marketing (Berinato 2018; Schrage & Kiron 2018). A manager might not understand the analytical methods used or the meaning of their outcome --- and might therefore not use the results in making a decision. At least he or she looks like a data-driven executive, fulfilling the expectation of their superiors and alleviating the pressure put on them (Davenport & Harris, 2017). As a result, though, many decisions are still driven by intuition, gut feel, or sketchy deductions --- which causes considerable frustration for the analytics team, as they soon realize their hard work (often conducted in addition to their regular duties) was only part of a "data as a cover my ass strategy".

It would be easy to blame those executives who are increasingly demanding data-driven solutions, but who do not take the time to have them explained in detail. Similar to an academic who frowns at the rejecting reviewer for clearly not recognizing the author's genius. In both cases, though, this behavior is not very effective. Instead, it might help to think about why the other side was not able to understand. Is there a better way of communicating my key message? Davenport and Patil's (2012) noted that while coding skills might become less relevant, one of the most enduring skills for data workers will be to "communicate in language that all their stakeholders understand --- and to demonstrate the special skills involved in storytelling with data, whether verbally, visually, or --- ideally --- both (p.73). The key is mutual understanding. On the management side, there must be a fundamental commitment to marketing analytics - and with it the will to engage in data-driven approaches. In addition, the analytics team must understand that an SQL database is not an adequate sales pitch to convince a c-suite - especially in marketing and advertising. Instead, insights must be communicated in a format that is easy to understand at all levels of the organization and that suggests a clear course of action related to the companies' challenges.

This is where many of the previous skills come together and need to be brought together in one consolidated effort. A graphically appealing story has to be told (storytelling), which answers the company specific challenge based on solid statistical insights (technical, theoretical & statistical expertise). At present, this "selling" of innovative ideas is still a problem, as pure analysis departments often lack the skills that bring them together (Berinato, 2018). In addition to strong expertise in the area of data visualization (for example with the help of tools such as PowerBI and Tableau), a generalist is also needed to ensure that there is a common thread to hold the story. As a project lead, this generalist not only has the needs of the company in mind, but can also ensure that work is targeted and there are no frictional losses in the various areas. However, such generalists (similar to the jack of all trades) are rare and often come from an academic environment or are at home in consulting.

Implementation: Now What?

The best concept is useless if it cannot be implemented. This applies not only to data-based marketing itself (as described above), but also to the "Five Pillars". Many initiatives to implement data-driven marketing fail because they are hailed as a panacea. These "moon shot"-projects, often designed to re-invent the entire business, are more likely to fail, though. Although the allure of a quick fix is understandable, it is also unrealistic. Potential changes to existing workflows might be difficult to implement within existing processes. Few companies can afford, for example, to create a new department, pull employees away from existing tasks, or re-structure existing workflows and processes. This is why managing expectations is key. Data-based innovation needs to be seen as a long-term project – not a sprint. Data teams should initially tackle smaller projects to achieve quick wins with "lower hanging fruits" that visibly enhance business processes (Davenport & Ronanki, 2018). This has been common practice with many technology-related adoption projects, but the hype and pressure surrounding analytics has led to an all-in mentality in many companies and agencies. For these smaller projects, it is easier to find volunteers with the necessary skills in the individual company divisions who want to work on an innovation project in addition to their actual work or at designated times (similar to the 20% rule at Google). In this way, initial results can be shown quickly, which then serve as a "proof of concept" and facilitate greater commitment from management.

It is also not a matter of how much (or what type of) data are analyzed and how sophisticated the underlying technology is --- even though current developments in the industry, where agencies out-buzzword each other about who has the bigger data lake and the more advanced algorithms, might suggest otherwise. What is much more important, is the dedication to these analytics efforts and a strong commitment to using the results to improve the business even in the face of uncertainty (Davenport & Harris, 2017). A positive example is Adidas' cross-departmental collaboration in North America, where brand marketing is working with eCommerce, product and other departments on a communication strategy for all touchpoints based on jointly developed insights (Budell, 2018).

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