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BUILDING ANALYTICS CAPABILITIES FOR GREATER OPTIMIZATION AND ROI

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Building Analytics Capabilities for Greater Optimization and ROI

All roads lead to data. Or rather, when it comes to insightful decision-making, optimizing operations, reducing costs, and outperforming competitors, all roads lead *with* data. Therefore, it should come as no surprise that nearly every Fortune 1000 company is somewhere on the long, rather arduous journey to–and heavily investing in–building its analytics capabilities.

If your business is also endeavoring on the path to adopting analytics in order to create greater value and achieve sustainable growth, this primer on building the right capabilities is meant to expedite your passage so you can successfully take advantage of the powerful learning resource that is data, while also *minimizing your analytics costs* and *yielding a stronger, faster ROI.*

First, we will introduce a series of questions to help you identify where your business currently resides on the journey to optimized data analytics, then we explore methods for elevating your data organization, and finally, discuss how you might apply all of this in determining what your business really needs....there is no one size fits all solution.

UNDERSTANDING DATA AND DATA ANALYTICS

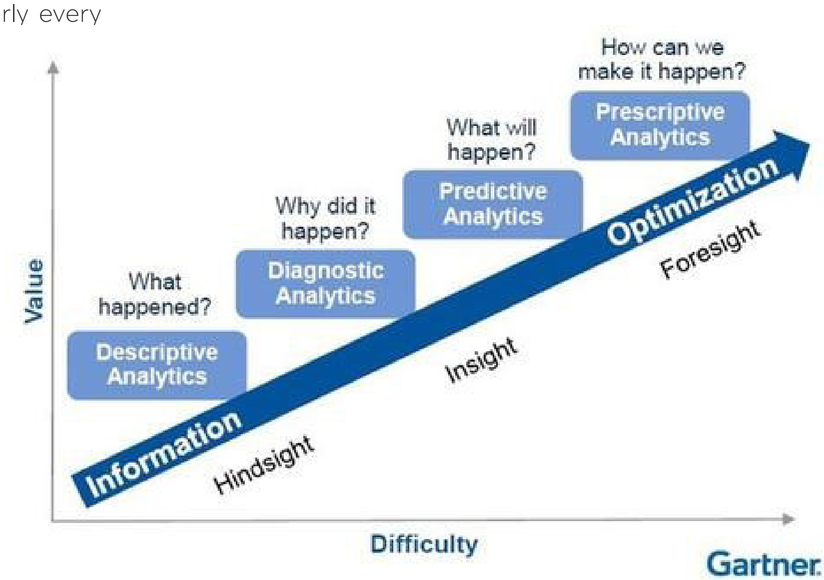
"A point of view can be a dangerous luxury when substituted for insight and understanding."
-Marshall McLuhan, philosopher, futurist, communications theorist

The analytics market (a.k.a. predictive analytics, data science, modeling, machine learning, model building, AI) is big and growing. And while some companies have still not fully integrated Data Analytics into their business strategy and operations, it is increasingly important for them to do so in order to be more efficient and agile in the market and build stronger relationships with customers.

Perhaps one of the first steps is for you identify where your business exists on the journey to optimized data analytics (i.e., how mature is your organization today?). Pundits often talk about the evolution and maturity of analytics organizations using the concept of Maturity Models. There are many variants out there from companies like IDC, Gartner, IBM, and others.

One such model from Gartner is shown here:

Gartner Data Analytics Maturity Model



But if you are in the early stages of your journey, how do you even get started? Analyzing all that data and assessing how to best leverage it is a first step in harnessing its power.

The questions laid out below are somewhat sequential in nature. For example, if you are unable to answer the first two questions with confidence you may have a long road ahead – but also meaningful opportunity (as detailed in subsequent sections).

1. ***What problem(s) am I trying to solve?***

   While this may sound trite, it is perhaps the most important question to ask for every data analytics project. Not only does this help define the scope of data and analytics required, at times, there are ways of infusing domain knowledge to simplify the solution or make it faster, better, and cheaper. For this reason, having domain skills on the analytics team is paramount.

2. ***How much and what kind of data does my business capture?***

   This will largely depend on what business problems you need to solve (see above).

   Take a look at the types of data your business collects (numerical data, video, text). Each has differing values, volumes, and storage requirements (e.g. clickstream data is high volume but usually not high value). High-value numerical data is generally stored in a data warehouse, while low-value, uncleansed data can be dumped into a data lake until it is needed. Worth noting: It's *not* unusual for an enterprise to maintain both a data warehouse and a data lake.

3. Is the data we are capturing, in fact, the kind of data we should be capturing to run our business effectively?

It is not always possible to collect ideal data as it simply may not be available. For example, it is vital for retailers to understand what consumers want to buy; however, consumers may not share this information directly due to privacy concerns. In this case, collecting proxies like Internet browsing and search histories that infer interest rather than explicitly state it must suffice.

So now, let us assume you have answered the first 3 questions to your satisfaction. Now you are ready to dive into descriptive and predictive/prescriptive analytics as depicted on the Gartner maturity model. For this, it is important to understand some building blocks that constitute these descriptive and predictive/prescriptive analytics.

4. What happens after data is captured?

ETL (Extract Transform Load) or Data Cleansing: Once data is collected and storage needs are identified, it is then important to cleanse and check data before it is stored. For low-volume (but high-value) numerical data, this is referred to as ETL (Extract, Transform, Load), and is run before data is loaded into a data warehouse or a data mart.

Data Warehouse vs. Data Mart: A data warehouse is an integrated, authoritative source of historical data for the entire enterprise. The data in a warehouse is assumed to be high fidelity and is often used for critical functions like reporting financial results to Wall Street. A data mart is a subset of a data warehouse and is limited in scope, usually dedicated to a function or department within a company.

Data Lake and Data Refinery: The ETL process can be bypassed for information that is high volume. In that instance, raw data can be dumped into a data lake until it is needed. Often data lakes are constructed using cheaper storage solutions given the volume of data they hold. Data in a data lake can be cleansed right before it is used or analyzed. Sometimes this cleansing process is called a data-refining process. The advantage of this approach is that you do not have to clean all the data, just the portion that you want to use.

*It is worth noting that building these data stores is perhaps the most capital-intensive part of the data function, and also takes the maximum amount of time to complete. Also keep in mind, data marts are faster and cheaper to build than data warehouses.

5. What happens after data is cleaned, stored, and available?

With data captured, cleansed, and stored, it is now time to extract value from it using a variety of Data Analytics tools:

Business Intelligence: Customizing reports in Excel or using reporting/visualization software* and other tools can track and transform relevant historical data (e.g. What were my company's revenues yesterday? How much did revenues grow from last quarter?) into insights that drive better decision-making. This constitutes "Descriptive Analytics" as shown on the Gartner maturity model.

*Microstrategy, Tableau, PowerBI, Cognos, Hyperion are a few examples of reporting and visualization tools.

Predictive Analytics: Armed with historical data, a "rear-view mirror" picture that tells a story of what has happened, look next at what *will likely* happen. Predictive Analytics provides further insights used for forecasting trends, potential risks, consumer behaviors, and other pertinent patterns. As an example, with this type of statistical analysis (using regression, clustering, and classification, etc.) businesses can try and predict annual revenues for the next fiscal year or identify potential new customer segments.

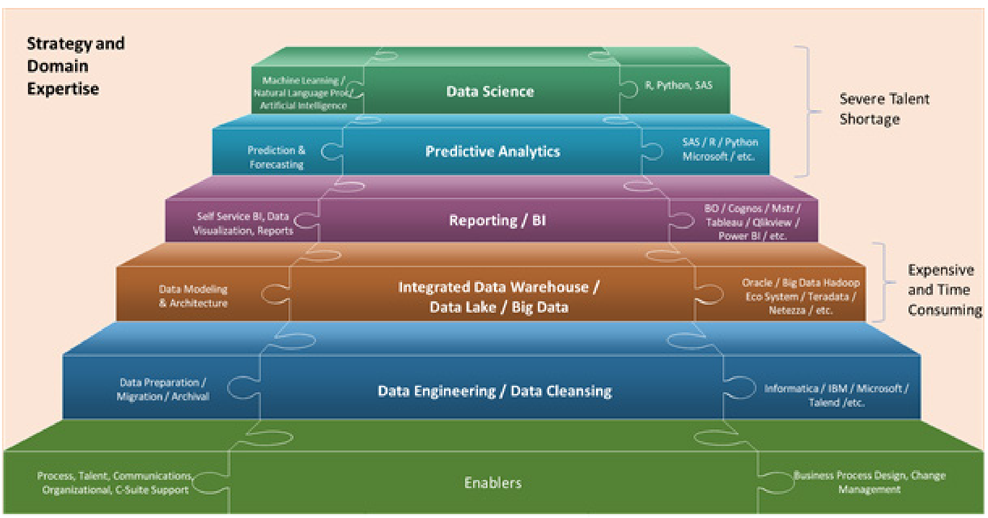
Data Science/Machine Learning/AI: And then there is big data. With it, standard statistical techniques simply do not work. This is mainly due to the size and sparseness of these large data sets. Therefore, techniques have been developed in Computer Science to address these issues. Machine Learning (ML) is a set of newer analysis techniques employed to build recommendation engines, conduct image analyses, and even perform natural language processing. AI (Artificial Intelligence) can ingest new data observations to train and improve an algorithm automatically. Deep Learning is an example of a Machine Learning technique usually employed for AI. While AI, Machine Learning, and Deep Learning are all buzz words, they are, in fact, used in less than 10% of data analytics conducted by most Fortune 500 companies.

R, Python and SAS are typically the tools used for Predictive Analytics, as well as Data Science/ML/AI. These two areas also represent the primary shortages of highly skilled talent.

Business Insights and Decision-Making: Once a report or model (predictive or AI/ML) has been built, it is critical to interpret the model and garner insights from it. It is often helpful to have business or domain knowledge to do this effectively. Once these insights are translated back into business terms, business decisions based on these insights can be made–either by humans or by computers. Sometimes this is also referred to as "Prescriptive Analytics" i.e. making actionable recommendations based on data.

These building blocks described above that constitute descriptive and predictive analytics are shown in the schematic below:

Building Blocks for a Data Analytics Organization



SUCCESS ENABLERS

If you are able to answer each question in the previous section with reasonable confidence, and feel excited about what your data org is achieving, then some optimization around the success enablers may be all that is needed. These foundational components are vital to have in place to achieve success and drive ROI. In fact, companies that have set up analytics programs and are looking to improve and mature them, spend a lot of time and resources on the following:

- **Process**: This includes DevOps (laying plumbing from data sources, through ETL, to a data warehouse); intake (fielding requests from business teams for analytics/reports); fail-fast mentality (try something quickly; if it doesn't work, move on rapidly); Agile processes, etc.

- **Talent**: The industry is facing an issue with talent. Good-quality predictive analytics and data science/ML/AI talent is extremely hard to find. Demand far outweighs the supply. Good leadership is required to discern among applicants in order to build the right team. This is another area where there is a shortage: Historically, companies have staffed analytics leadership roles with general athletes or used these positions as parking lots for star performers from other areas. This approach quickly backfires. Another challenge is finding domain skills and analytics skills within the same individual. Rare.

- **Communications Skills:** Communication skills are important for many functions in a company; analytics is no exception. Once a model is built and insights derived, the business implications need to be communicated back to business leaders. The ability to glean insights and tell a compelling story are important skills and practices.

- **Change Management:** Functioning in a data-centric paradigm is new for most companies. Therefore, appropriate change management processes–usually with oversight from a PMO–need to be set up in order to revamp internal processes (including initiating requests for data-based insights and leveraging insights from such analyses) and shift the culture.

- **Executive Support:** Especially for young analytics organizations, support from the C-Suite is important to achieve broader adoption within an organization. Some leaders still resist the shift to data with unfounded arguments. Another reason is budget: Getting an organization's data infrastructure right is not cheap. Fortunately, with the attention data analytics has received recently, buy-in is more easily achieved today than in the past.

- **Organization:** Deciding where analytics functions live and what the reporting structure is are both vital. Data analytics almost always requires technical skills, whether software/IT skills on the data side (data warehouse, data lake, tools, infrastructure), or math/computer-science skills on the modeling side (BI, Predictive Analytics, ML/AI). For this reason, it is easy to put a data analytics organization under IT. However, data analytics is a business function, with a strong domain and business results focus (top line/bottom line). This raises an interesting dilemma for where the data team should sit within the organization. Companies have tried several options in lieu of having it report into the CIO's organization, e.g. reporting directly to the CEO, Chief Strategy Officer, Chief Marketing Officer, Chief Financial Officer, or to business unit leads.

THINK FIRST, THEN BUILD WHAT IS NECESSARY. NO MORE, NO LESS

For companies seeking to build out their analytics capabilities, it is important to consider any and all business goals and implications, and then attain alignment on them in the form of senior management support and enterprise buy-in. This is far from trivial, and businesses face many challenges in this area. Prioritizing data in long-term and day-to-day business decisions can be somewhat of a profound cultural shift, so understanding its impact–and as importantly, the necessary internal resources with appropriate domain knowledge and experience to support a data analysis program–is critical.

Once business issues and objectives are identified, and a decision to form an analytics team has been made, a highly skilled team should be formed, and the right techniques and approaches need to be established. Similarly, if you have a situation where your organization has built a little bit of everything, but is not close to optimal, you need to be judicious about where you spend your resources. Is everything required? Do you need to be a company like Google, Netflix, Tesla? Do you really need AI-based video analytics capabilities for instance? Likely not, but as you think about building your capabilities, it is imperative to ask whether or not you need all possible data and analytics capabilities. And while this answer is also likely *no*, an expert team will yield the best possible business results. More specifically, a team that has the right analytical and data science skills, and grasps the problem and understands how the two connect.

Critical to remember is, based on the unique needs of your company, not every rung or stair-step on any maturity model needs to be built out to perfection. In an ideal world, perhaps they would be. In the real world with budget constraints, time constraints, and talent shortages, it is not practical.

For companies facing serious budget/time/talent constraints, and trade-offs, here are a few options to consider:

- **Data Storage:** Building a data warehouse can take several months (often more than a year) and can cost several millions of dollars for a Fortune 500 company. Can you get started by building a smaller data mart first? Sometimes, it is even advantageous to do this in parallel with a large data warehouse project. Building data marts is usually not throwaway work and can get you started with reports and analytics much faster–and at a fraction of the cost.

- **Analytics/ML Talent:** If your organization does not have the right number of data scientists, could you consider hiring vendors, either on-shore or off-shore? If you need to hire full-time staff, and it is tough to lure data scientists away from the competition, could you engage recent grads or absorb talent from other departments and train them? Your business' approach will depend on its specific situation and needs.

- **Infusing Domain Knowledge:** Defining the business problem crisply has several advantages: One can potentially simplify the problem and hence alleviate the burden on building complex AI/ML models. Not all solutions require 100% automation and 100% accuracy. Moreover, it is possible to use human intervention, particularly with domain knowledge, to improve the accuracy of algorithms dramatically (the accuracy of NLP algorithms can rise from ~65% to ~90% with the infusion of domain knowledge).

Whether you build your own team, hire new grads, or outsource, it is important to keep in mind that you do not need to be an expert in every aspect of any maturity model. You may, in fact, start seeing results faster and at a fraction of the cost by employing some clever workarounds like the ones mentioned above, and getting all the Success Enablers right. You might even pursue these workarounds while your company builds a more robust solution in parallel. Most of your work will not be in vain, and the benefits from seeing results faster are immense!

In today's ultracompetitive global market, businesses simply don't have the luxury of waiting to integrate data analytics or investing high dollar amounts in these capabilities before experiencing ROI. And while resourcing the pursuit of data can be immense on many levels, by asking the right questions, making thoughtful choices, and adopting workarounds, you will be on your way to exploiting all that data has to offer and transforming how you do business.

ARTICLE AUTHOR

UJJWAL SINHA is an analytics and business intelligence specialist and senior executive with a top-tier consulting background from McKinsey & Company. He has extensive experience in analytics, data sciences, software engineering and operations, P&L management, and strategy. Most recently Ujjwal served as Vice President of Enterprise BI and Analytics for Target, where he led a global, 500+ person analytics team responsible for all BI and analytics operations for the company. Prior to this, he served as the Vice President of Strategic Operations for Salesforce.com, and held multiple Director-level roles at Microsoft across product management, marketing, and strategy. Earlier in his career he served as an engagement manager at McKinsey, as President of Swift Rivers, a developer of cloud-based BI solutions for the retail industry, and as Vice President of Strategy & Analytics for Digitas.

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