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Strategies for Scaling Analytics: A Nontechnical Perspective

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ABSTRACT

Nowadays, many organizations are trying to scale up their use of analytics to become data-driven. The vision is to make better decisions based on collected and analyzed data. However, doing this is not trivial.

In our experience, a typical scaling scenario implies conducting a technical pilot project on predictive analytics, introducing a more advanced analytics platform, and hiring data scientists (or AI programmers). It does not usually include developing strategies for nontechnical aspects. Organizations that follow this process will encounter many of the already well-known barriers, such as business resistance and lack of management support.

In this article, we present a guide to scaling up analytics for analytics leaders with a special focus on the nontechnical aspects of the task. The journey starts by investigating and improving the competence and skills in a current cross-functional group before an overall scaling plan with supporting strategies is developed.

INTRODUCTION

In the last decade, advanced analytics and data-driven organizations have frequently been promoted as the next step for organizations (Davenport, 2018; LaValle, Lesser, Shockley, Hopkins, and Kruschwitz, 2011; McAfee and Brynjolfsson, 2012). The golden nugget is to use more advanced forms of analytics (such as predictive or prescriptive analytics) to make better decisions and become data-driven. Organizations that have managed to embrace and scale up the usage of advanced analytics are typically in better positions than their competitors with respect to financial and operational results (McAfee and Brynjolfsson, 2012).

However, not all organizations manage to reach a data-driven stage—at least not yet. Out of 72 *Fortune* 1000 companies that participated in the 2020 survey by New Vantage Partners, 37.8% claimed they had created a data-driven organization, while 26.8% had managed to establish a data-driven culture (Bean, 2020, see Table 1). Compared to previous years, the trend for having a data-driven organization in place has been declining between 2017 and 2019 but increased for 2020. Although only two measures are available regarding having forged a data-driven culture, the trend is declining.

It is well known from the literature (Halper and Stodder, 2017; LaValle et al., 2011) that the barriers to becoming data-driven are mostly nontechnical. However, we have seen that this insight is ignored in practice. We have encountered several analytics professionals and consultants who too often focus on technical aspects such as choosing the most relevant data management methodology or the right BI front-end tool for the use case currently in scope.

	2017	2018	2019	2020
Have created a data-driven organization	37.1%	32.4%	31.0%	37.8%
Have forged a data-driven culture			28.3%	26.8%

Table 1. Organizations that have established a data-driven organization and a data-driven culture.

This is a convenient conclusion because it is a call for action. We feel good when starting new initiatives because we feel we're doing something about the situation. A technical project is concrete and visible in the organization. However, if we had problems before—for example, data quality issues or problems with analytics adoption—it is not certain that introducing a new BI front-end tool will solve those problems. Sandkuhl (2019) recently made a similar observation that organizations too often take a technical focus when adopting AI into an organization.

Previous investigations (Berndtsson, Lennerholt, Svahn, and Larsson, 2020; Davenport and Bean, 2018; Fleming, Fountaine, Henke, and Saleh, 2018; Halper and Stodder, 2017) paint a picture where most top barriers are nontechnical, such as pilot projects not being adopted by the business, random, uncoordinated AI projects dotted all over the organization, and no use of a systematic process in place.

How can we scale use of advanced analytics more systematically and at the same time avoid the major nontechnical barriers for becoming data-driven?

STEP 1: RAISE COMPETENCE AND SKILLS IN A CURRENT CROSS-FUNCTIONAL GROUP

Before a bigger analytics initiative is proposed and launched, reflect on the current competence and skills in analytics in a cross-functional management group where you participate.

Descriptive analytics is the foundation for introducing advanced analytics, so ensure that the group's skills in descriptive analytics and data literacy are not deteriorating. For example, to what degree are self-service business intelligence tools used within your teams, such as PowerBI, Tableau, or Qlik? Use of self-service business intelligence tools is one of the enablers for a data-driven organization. Having personal experience with such a tool is good.

Keep in mind that not all managers have a brief understanding of what is meant by "business intelligence," "advanced analytics," and "data-driven organizations." We have come across managers who are ashamed to acknowledge that they have only a very vague understanding of what is meant by these terms. As an analytics leader, you can point people in the right direction to help them to refresh their understanding. We highly recommend Anderson (2015); Chaudhuri, Dayal, and Narasayya (2011); Chen, Chiang, and Storey (2012); Davenport and Harris (2007); and Dearborn (2015).

As an analytics leader, you can start to coach other group members to have a data-driven mindset at your present meetings. For example:

- Ask the right questions (e.g., what analytics/data were used?) (Watson, 2016)
- Use interactive tools instead of paper reports (Wixom, B., and Relich, 2013) and walk the talk
- Coach yourself and others with the analogy of a picture postcard (Berndtsson, 2019)

A data-driven approach to decisions in meetings implies an open discussion where members debate directions to take based on analyzed data. If the group dynamic is poor and backfires, backtrack and use inspiration from

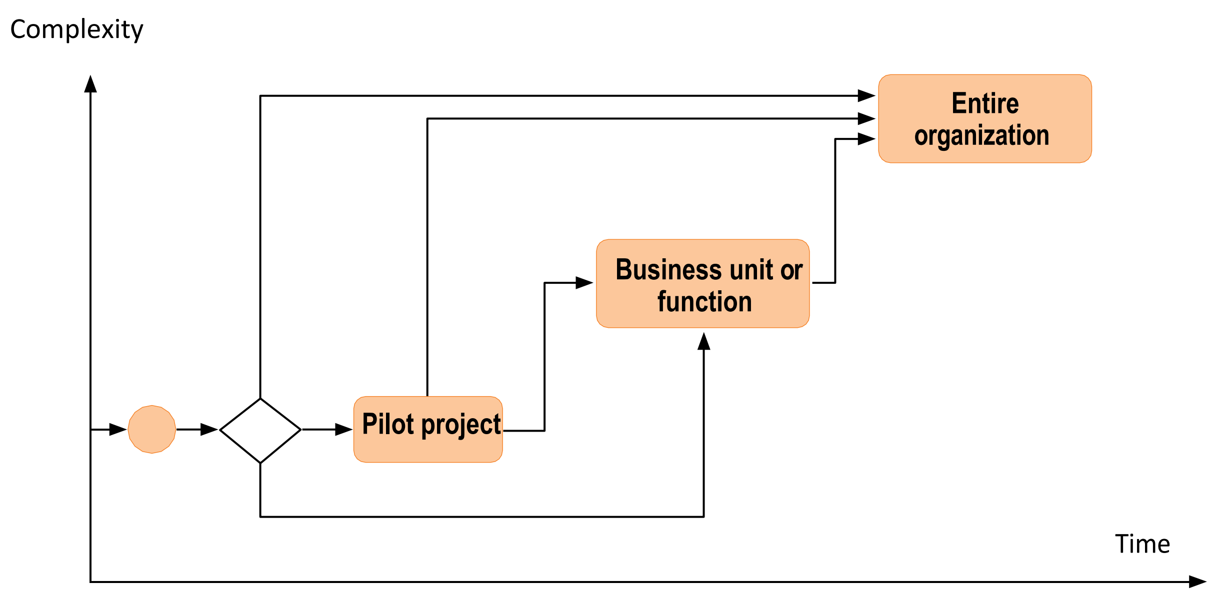

Figure 1. Scaling paths.

sources (such as Lencioni (2002) and Marquet (2020)) to improve the decision-making culture within the team. Focus on "what does the data tell us?" and avoid decisions based on "gut feeling" or "I have the most power in this room, therefore I decide."

When looking for data for your decisions, you often end up with financial data and simple quantified data such as number of employees or total sales, depending on the nature of your business. This data is fine to answer questions such as "How did it go?" or "Why did it happen?", but do not settle on that. More important is to look for data that can provide insight about the future. For example, if your customer satisfaction goes down, it is highly likely that your profits will go down in the future. If your attrition rate skyrockets, you may have a corporate culture problem that needs to be addressed. This is also a case for moving beyond descriptive analytics and into predictive and prescriptive analytics. There are several gold mines of data within your organization. Just go find them.

As a simple exercise, keep track of how often you derive business insights in your group from collected data and respond to what the data suggests.

The purpose of the first step is to get first-hand experience with applying a data-driven mindset in a cross-functional group, where other members are likely to have lesser skills in analytics than you.

STEP 2: DEVELOP AN OVERALL SCALING PATH

The next step is to develop an overall scaling path that specifies which path to take, what analytics should be scaled up, and what type of decisions should be addressed.

Scaling the use of analytics to become a data-driven organization takes place among four major paths (Berndtsson et al., 2020), shown in Figure 1:

- Pilot project first, then incrementally scale to business units or business functions before targeting the entire organization
- Pilot project first, then target the entire organization
- Business unit (or business function) first, then target the entire organization

		Advanced analytics		
	Descriptive analytics	Predictive analytics	Prescriptive analytics	
			MANUAL	AUTOMATED
Top-level management decisions				
Middle management decisions				
Operational decisions				

Table 2. Type of analytics versus type of decisions.

Typo in Table 2 corrected after publlication

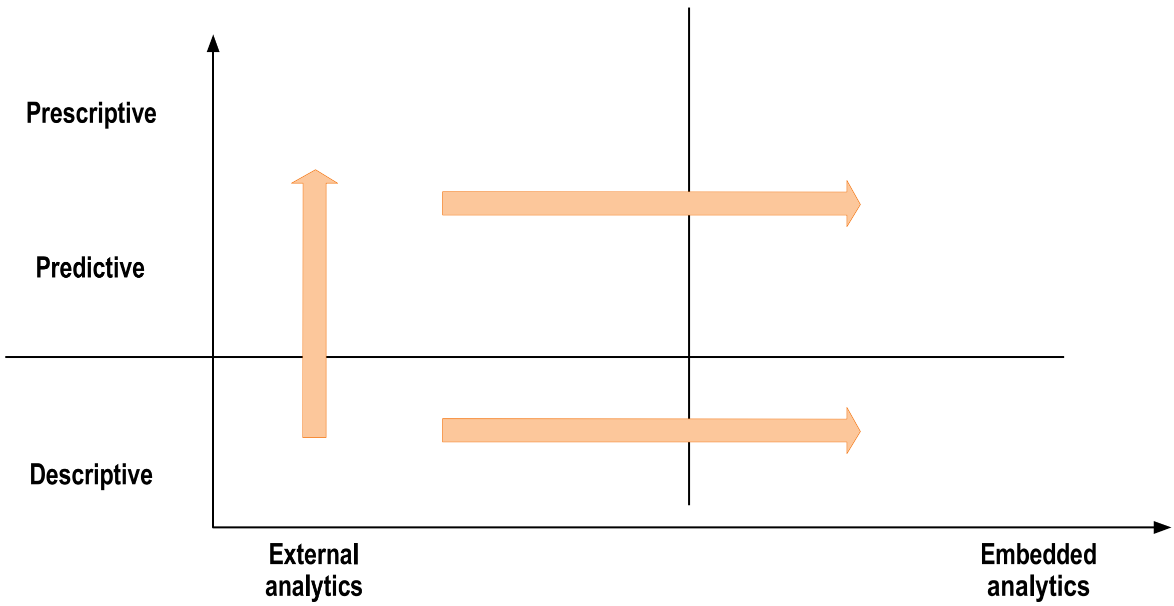

Figure 2. Type of analytics versus embedded analytics.

o Entire organization

As the scaling within the organization continues, the more complex and time consuming it becomes. In our experience, most organizations aim for the safe paths and start with a pilot project before trying to scale further. We have seen organizations that successfully ran several pilot projects in parallel but not several business units in parallel.

Analytics is used to make better decisions, and scaling analytics is a journey that is done in several dimensions, as shown in Table 2. First, determine what types of analytics should be scaled and for which types of decisions.

All scaling attempts with analytics start with a solid use of descriptive analytics in place. Do not take a shortcut and jump directly to prescriptive analytics without having both descriptive analytics and predictive analytics in place. However, there is nothing wrong with starting to conduct tests on a smaller scale just to get an idea of what it will take to do it on a larger scale.

In our experience, most organizations tend to start with a specific business question or problem at the operational decision level. Apart from the books by Jennifer Dearborn that are loosely based on real cases, few organizations seem to start with scaling analytics for decisions that are made at the middle-management level. Even fewer sources describe organizations that had top-level management as the starting point.

Another dimension of scaling is to consider to what extent analytics is embedded into applications used in the business process (see Figure 2). In the simplest situation, descriptive analytics is performed with a separate tool (such as a spreadsheet) and the business process uses a different application or tool. This is in contrast to an approach where the analytics is embedded in the business process application.

Once a rough path is in place, an overall change management process should be selected. Using an overall change management process helps the organization stay on track with its initiative. The respondents in a survey conducted by Forbes-Insights and EY (2015) claimed that change management was critical to their success in scaling analytics. In our research, we investigated 13 organizations and none of them used an overall change management process. As a consequence, many of them struggled with barriers such as business resistance and insufficient organizational alignment.

STEP 3: DEVELOP NONTECHNICAL STRATEGIES

Most organizations have technical strategies in place for data, tools, and technical platforms. Similar strategies for nontechnical aspects are less common. Nontechnical strategies need to be developed to avoid or reduce the following major barriers (Berndtsson et al., 2020):

- Lack of understanding and business resistance
- Lack of skills
- Insufficient organizational alignment
- Lack of senior management support
- Lack of corporate strategy
- Lack of middle management adoption and understanding

The question is then what type of nontechnical strategies should be developed? One answer is to develop nontechnical strategies with respect to a generic analytics framework. The advantage is that the analytics framework can act as a check if some strategy is missing. For this article, we use an adapted version of the frame-

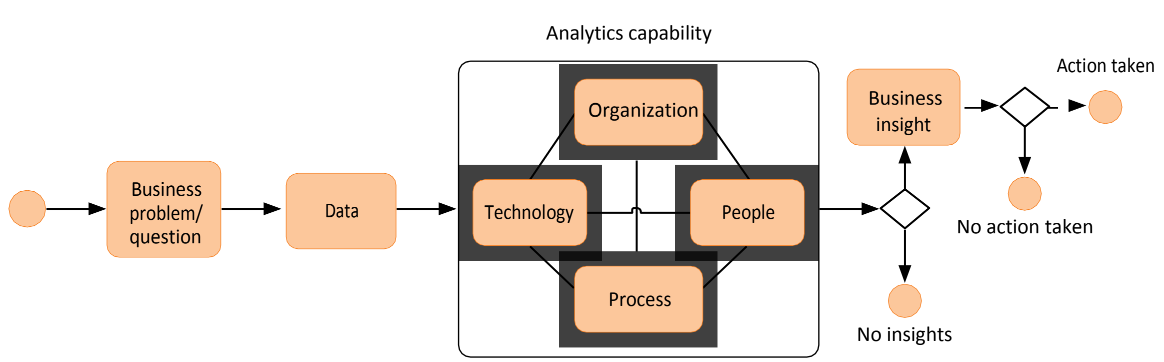

Figure 3. A sample framework for analytics.

work in Berndtsson et al., 2020 and Vidgen, Shaw, and Grant, 2017, shown in Figure 3.

In the next sections, we will examine what nontechnical strategies should be developed depending on the position in the scaling path (Figure 1) and the analytics framework (Figure 3).

PILOT PROJECTS

A pilot project in analytics can run smoothly and produce new insights that—in some cases—can produce business value quickly. However, it can also stir up emotions among employees and invoke well-known barriers such as a lack of middle management adoption and understanding or a lack of understanding along with business resistance. It is not uncommon that employees feel threatened by pilot projects in advanced analytics because the project is considered as a threat to their salary, decision-making power, and job.

An approach to defusing wrongly set expectations and fears is to run a *Hopes and Fears* exercise. Hopes and Fears is an exercise that can be used at the start of a project to investigate group members' hopes and fears about a change. Participants are asked to write down their hopes and fears about the change on Post-It notes, and place them in quadrants shown in Figure 4. Visions are hopes that are unlikely to occur, and they can be ignored. Goals are likely to occur, and they should be prioritized if they are too many. Nightmares are fears that are unlikely to occur and can be ignored. Fears that are likely to occur need attention and action plans.

For example, if several group members fear that "being data-driven" implies that all decisions will be automated, then address that topic in a separate meeting. Similarly, if several group members have written down exceedingly high

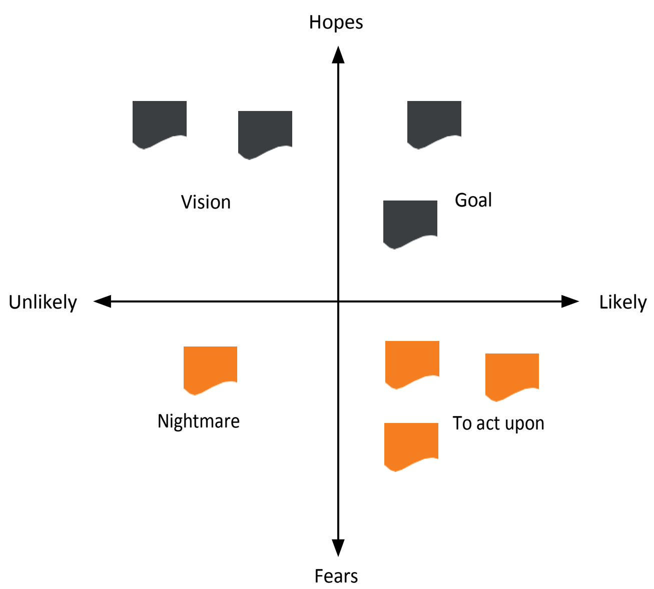

Figure 4. A Hopes and Fears exercise.

expectations and hopes about what it means to be data-driven, that becomes visible as unrealistic goals. If these expectations and fears are not addressed in the beginning, they will later undermine the initiative, for example, as business resistance to participate and share knowledge.

After a successful pilot, share the findings and scale the use of analytics to a bigger audience within the organization. Senior management usually acts as gatekeepers to funds and resources whenever an attempt is made to scale analytics beyond a pilot project. If senior management is already leading by example and is sponsoring an analytics initiative, then it is full-steam-ahead to the next level. However, if senior management is hesitant about or resistant to advanced analytics, you need to have a plan for how to reduce their resistance.

To reduce resistance in a pilot project and secure approval from senior management, use mechanisms from change management. If the organization is taking the *pilot-first route*, ensure that the pilot has a convincing business case (a specific business problem or question in Figure 3), which creates both emotional and rational buy-in (Cohen, 2005). Findings from the pilot should be visualized and experienced by people who were not part of the pilot project. Furthermore, because the pilot project is part of a bigger picture, align the pilot project to existing business strategies (Bisson, Hall, McCarthy, and Rifai, 2018; Franks, 2014) and use a cross-functional team (Kotter, 2012).

A cross-functional team is critical for establishing trust between the business side and the IT/analytics side. There are too many stories reported in the literature where a pilot project was set up with mostly data scientists that produced valid results but that in the end were not adopted by the business side due to a lack of trust and lack of involvement.

BUSINESS UNIT (OR BUSINESS FUNCTION)

Once a suitable business unit (or business function) has been selected, let a cross-functional team develop a vision and supporting strategies, or refine existing vision and strategies. Actively discuss the vision and supporting strategies with all stakeholders before, during, and after they have been developed.

With respect to the framework in Figure 3, nontechnical strategies should be developed for:

- Fostering a culture where business problems and questions are spontaneously generated for further investigation with the aid of analytics. For example, develop forums and channels for collecting business problems and questions that should be further investigated by analysts.
- Organizing analytics competence and how such a unit should interact with the business side including existing units such as business intelligence competency centers. An overview of different approaches is presented in Harris, Craig, and Egan (2009).
- Determining how employees should work with analytics in existing decision processes.
- Raising employees' skills and competence in analytics and what it means to have a data-driven, decision-making culture.

For example, a suggestion for raising employees' skills and competence in self-service business intelligence was presented in Berndtsson, Lennerholt, Larsson, and Svahn (2019).

Furthermore, many organizations and institutions have raised the concept of data literacy. This could be summarized as learning the language of analytics so as to be able to interpret data, graphs, reports, and dashboards, draw conclusions, and understand what actions to take. Currently, many organizations are adopting data literacy programs. The programs often start with a diagnostic test to find out the current level of data literacy, then they move on to include practical training, exercises with relevant data for the employee, and coaching sessions.

- Raising employees' buy-in for using analytics. One approach is to introduce incentives for using analytics in the decision process or completed analytics education. Another approach is to introduce "analytics ambassadors" who fully embrace the concepts of analytics and help others to see the advantages of becoming data-driven. These ambassadors are often enthusiastic and highly influential. If they happen to be high-level managers, these ambassadors are even more important for analytics adoption.
- Identifying how business insights are documented, shared, and rewarded.

Finally, increase leadership training for employees (Lencioni, 2002; Marquet, 2020). Introducing a data-driven approach to decision making is likely to move the decision power closer to the front line of the business. Thus, more people are likely to be part of making decisions. Furthermore, decisions in a data-driven culture require an open and trusting culture, where decisions are not based on gut feeling or a top-down approach. An outdated leadership style will halt any attempts to be more data-driven in practice.

THE ENTIRE ORGANIZATION

Reaching the enterprise level implies that all business functions and all types of decisions should have a data-driven mindset in decision making. This will require nontechnical strategies for:

- Establishing an in-house BI and analytics academy that educates employees on a bigger scale and in more depth
- Establishing analytics career paths
- Establishing a program for data literacy, raising analytical capabilities for employees
- Sharing your knowledge about BI and analytics at business events and in research projects with universities
- Determining the minimum number of BI and analytics experts each department or unit should have
- Ensuring that the use of analytics is not going back to "gut feeling"
- Selling (or sharing) collected data or generated insights

Do not underestimate the need for change management to get everybody onboard. Just providing tools is not sufficient.

An executive who was interviewed in Davenport, Harris, and Morison (2010, p. 147) noted that "you can't change a culture by creating a department." In other words, having established a data-driven organization with the appropriate analytics departments and with strategies in place does not necessarily imply that a data-driven culture has been established in practice. This is also evident in the annual reports from New Vantage Partner, where the percentages for "established a data-driven culture" are always (so far) lower than "established a data-driven organization."

A FINAL WORD

The phrase "culture eats strategy for breakfast" is perhaps true, but without a strategy for scaling nontechnical aspects, there is only a technical strategy to eat and digest for the employees. Such an organization will encounter several of the already well-known barriers to scaling up analytics. With nontechnical strategies in place, there is at least a chance to reduce and avoid some of the barriers.

That said, a strategy is great, but action is even better. The strategy should point you in the right direction and give insights into which actions to take and when. In this article, we have offered concrete advice about which actions and programs to develop in order to make your organization more data-driven. ●

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