Hype Cycle for Analytics and Business Intelligence, 2019

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Initiatives:Analytics, BI and Data Science Solutions

This Hype Cycle will help data and analytics leaders modernize their analytics and BI programs. Key trends include the ongoing transition to augmented analytics, focus on building a digital culture, and the scaling and operationalization of analytics initiatives.

More on This Topic

This is part of three in-depth collections of research. See the collections:

- Research Guide to Introducing Analytics and Business Intelligence in Legal Departments
- How Augmented Analytics Will Transform Your Organization: A Gartner Trend Insight Report
- 2019 Hype Cycles: 5 Priorities Shape the Further Evolution of Digital Innovation: A Gartner Trend Insight Report

Analysis

What You Need to Know

Analytics and business intelligence (BI) continues to reign as a top IT and business leader innovation investment priority as intelligence is at the core of all digital businesses. However, the expanded and strategic role of data and analytics is pushing the limits of current capabilities. The ongoing visual data discovery vendor consolidation highlights that we are now clearly in the third wave of analytics and BI, referred to as augmented analytics. This generation is being driven by the need to consumerize insights across all business roles. Whereas visual data discovery made analytics easier for business analysts, the focus of augmented analytics is making it easier for business consumers to get answers. Augmented analytics uses natural language processing and conversational interfaces, allowing all users to interact with data and insights without requiring advanced skills. And, it automates aspects of finding and surfacing the most important business insights and provides contextualized recommendations to optimize decision making. “Consumerization” also means that augmented analytics capabilities are increasingly being embedded in enterprise applications, eliminating the need for users to have to switch context and learn new tools. And, the push to proliferate insights is highlighting the language barrier between data and analytics creators and consumers, and the need to increase data literacy across the organization.

Eight Hype Cycles for 2019 cover the technologies, architectures and frameworks for data and analytics. Together, they contain the necessary elements for data and analytics leaders to form this holistic view.

Hype Cycles Covering Data and Analytics

- "Hype Cycle for Analytics and Business Intelligence, 2019"
- "Hype Cycle for Artificial Intelligence, 2019"
- "Hype Cycle for Back-Office Analytic Applications, 2019"
- "Hype Cycle for Customer Experience Analytics, 2019"
- "Hype Cycle for Data Management, 2019"
- "Hype Cycle for Data Science and Machine Learning, 2019"
- "Hype Cycle for Enterprise Information Management, 2019"
- "Hype Cycle for Data and Analytics Governance and Master Data Management, 2019"

The Hype Cycle

This year's Hype Cycle reflects five key trends impacting the analytics and BI market:

- **Augmented Analytics** is defined by the use of automation, machine learning and natural language processing to:
  - Speed up the time to prepare data.
  - Automatically find patterns in the data.
  - Communicate the analytical findings to a broad set of users using natural language generation and a variety of user interfaces.
- **Digital Culture** reflects three subtrends:
  - Data literacy is critical to digital transformation and overall digital dexterity.
  - Digital ethics and privacy are growing concerns for individuals, organizations and governments.
  - Enterprise and vendor data-for-good initiatives rising as part of social investing and calls from consumers and employees for companies to focus on social purpose.
- **Relationship Analytics** highlights the growing use of graph, location and social analytics to understand how different entities of interest — people, places and things — are related, and enables deeper insights that are closer to human knowledge representation.

- **Decision Intelligence,** an emerging practical discipline framing a wide range of decision-making techniques — continuous intelligence, decision automation and event stream processing — supports a dynamic and increasingly complex business environment in perpetual motion.
- **Operationalizing and Scaling** involves how to more effectively operate in a bimodal manner. This, in turn, involves balancing agile and flexible analytics needs to react to changing business needs with production-grade analytics that need to be governed.

Data and analytics leaders should study the swarm of innovations at and near the Peak of Inflated Expectations to understand the potential of these technologies in their organizations, but cautioned to not get caught up in the hype. Innovations such as augmented analytics have the potential to speed up the time to analyze data, reduce human bias and broaden access to advanced interactive analysis for business users and nonusers of traditional BI tools. Natural language interfaces such as search, text and voice are making analytics more accessible by a broader set of users. And, explainability is increasingly becoming an important capability to give users confidence in using machine-generated recommendations.

Analytics teams should pay close attention to the data lakes innovation, which entered the Trough of Disillusionment this year. There is significant confusion about what a data lake is, how it compares to concepts such as data warehouses and data hubs, and how it supports different user groups and service-level agreements. Many data lake implementations are being designed to serve too broad a set of users: data scientists, business analysts and casual users. Because many implementation technologies aren't optimized for these kinds of diverse workloads, organizations are experiencing challenges with data and analytics governance, data quality and overall performance.

There is also an interesting cluster of innovations in the Trough of Disillusionment and toward the Slope of Enlightenment and Plateau of Productivity. Analytics and BI platform as a service remains in the trough, but organizations are beginning to understand when and how to deploy more of their analytics in the cloud. Organizations are also getting business value using a variety of advanced techniques such as location, predictive, social, and text analytics. And, visual data discovery has moved even farther to the right on the Plateau of Productivity as the market has become mature and standardized.

Several new and interesting innovations appearing in this year's Hype Cycle, including analytics catalog, data literacy and explainable AI, have the potential to help organizations better operationalize and increase the analytical insights to make decision making more data-driven. These are discussed below.

New Entrants

- **Analytics Catalog:** Combines portallike capabilities with curation and collaboration functions, enabling users to share, find, search, comment and rate dashboards, reports and datasets from a diverse range of platforms in one place. They also help those managing portfolios of analytics and business intelligence (ABI) platforms to monitor, manage and migrate usage.

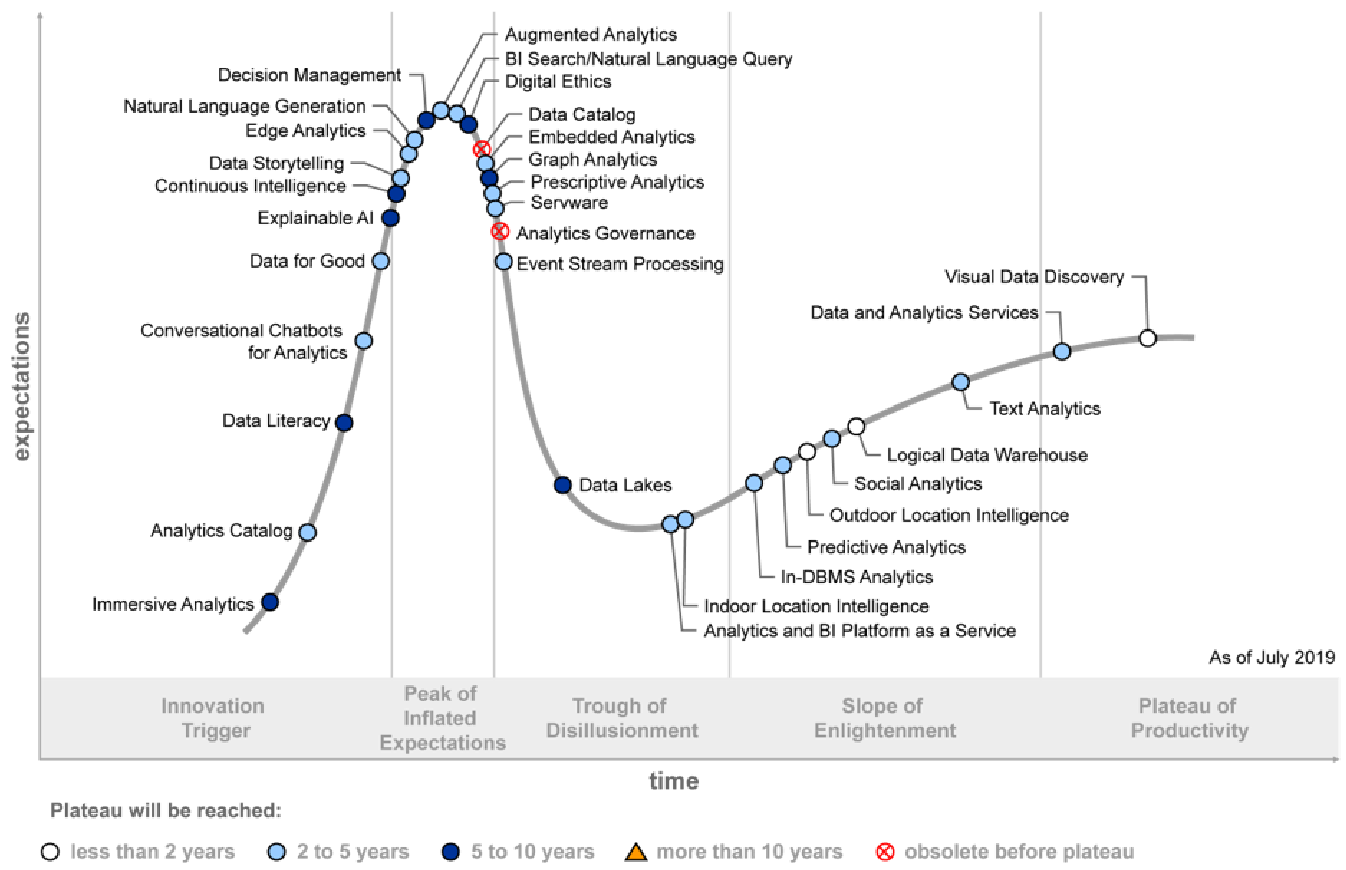
- **Data Literacy:** Defined as the ability to read, write and communicate data in context, with an understanding of the data sources and constructs, analytical methods, and techniques applied, as well as the ability to describe the use-case application and resulting value.
- **Data for Good:** A movement in which people and organizations transcend organizational boundaries to use data to improve society. The data usage may be within an ABI context or in more sophisticated data science and machine learning use cases, but the purpose is focused on social impact.
- **Explainable AI:** A set of capabilities that describes a model, highlights its strengths and weaknesses, predicts its likely behavior, and identifies any potential biases. It can articulate the decisions of a descriptive, predictive or prescriptive model to enable accuracy, fairness, accountability, stability and transparency in algorithmic decision making.
- **Indoor Location Intelligence:** Services and solutions that generate, process and analyze data in an indoor environment to provide insight on the location (and movement) of objects and people from a historic, real-time or predictive perspective. The underlying technologies are wide ranging and include Wi-Fi, Bluetooth Low Energy (BLE), infrared, ultrasound, RFID and ultrawideband (UWB).
- **Outdoor Location Intelligence:** The process of deriving meaningful insight from outdoor geospatial data relationships — people, places or things — to solve particular challenges such as demographic analysis, store placement, asset tracking, environmental analysis and traffic planning. This consists of a combination of geographical information system (GIS) software, web mapping solutions, position technologies such as GPS and location-based data.

Name Changes

- **Analytics and BI Platform as a Service (formerly Cloud ABI).** The new name better reflects the concept of cloud-native analytics and BI application infrastructure and software services.
- **Edge Analytics (formerly IoT Edge Analytics).** The new name is shorter and better captures that edge analytics is applicable to a wider range of use cases.

Figure 1. Hype Cycle for Analytics and Business Intelligence, 2019

Hype Cycle for Analytics and Business Intelligence, 2019



Source: Gartner
ID: 369713

The Priority Matrix

To help organizations prioritize investments in relation to their level of impact, we provide a Priority Matrix(see Figure 2). Note, however, that impact is not the only factor to consider when selecting vendors and products — applicability, budget, time to implement and receive payback, and return on investment are also important. The Priority Matrix shows the degree of benefit attainable relative to an innovation’s progression along the Hype Cycle.

“Transformational” benefit innovations can change the way organizations interact with information to such a degree that they have a demonstrable impact on organizations’ business models. Although it will take time, several innovations, including augmented analytics, event stream processing, continuous intelligence and immersive analytics, offer the potential to have a transformational impact. For example, augmented analytics can help organizations address analytical skill gaps through use of automation and embedded machine learning to prepare datasets, analyze variables for explanatory or predictive power, and decide how to visualize and present data.

“High” benefit innovations are less likely to change an organization’s business model, but they will have a significant impact on its analytics and BI program. Many of these innovations — such as conversational chatbots for analytics, data storytelling, natural language generation and BI search/natural language query — will provide high benefits during the next two to five years. In particular, predictive analytics will help organizations mature beyond descriptive and diagnostic analytics, and BI search/natural language query will make it easier for less sophisticated workers to get answers from analytics tools.

Although it may take five to 10 years for them to achieve mainstream adoption, innovations such as data literacy, decision management, digital ethics and graph analytics will greatly benefit analytics and BI programs. These innovations are more strategic and require long-term planning and investment. Innovations in this group enable improvements to broaden analytics and BI initiatives across the organization.

Figure 2. Priority Matrix for Analytics and Business Intelligence, 2019

Priority Matrix for Analytics and Business Intelligence, 2019

benefit	less than 2 years	2 to 5 years	5 to 10 years	more than 10 years
transformational		Augmented Analytics Event Stream Processing	Continuous Intelligence Immersive Analytics	
high	Logical Data Warehouse Outdoor Location Intelligence	BI Search/Natural Language Query Conversational Chatbots for Analytics Data and Analytics Services Data Storytelling Edge Analytics In-DBMS Analytics Indoor Location Intelligence Natural Language Generation Predictive Analytics Prescriptive Analytics Serverware Social Analytics	Data Literacy Decision Management Digital Ethics Explainable AI Graph Analytics	
moderate		Analytics and BI Platform as a Service Analytics Catalog Data for Good Embedded Analytics Text Analytics	Data Lakes	
low	Visual Data Discovery			

years to mainstream adoption

As of July 2019

Source: Gartner
ID: 369713

Off the Hype Cycle

- **Artificial General Intelligence** was dropped as the innovation is more relevant to the Hype Cycle for AI and Hype Cycle for data science and machine learning.
- **Data Preparation** was dropped as the innovation has become a standard capability of nearly all analytics and BI platforms.
- **Geospatial and Location Intelligence** was replaced with two new innovation profiles (Indoor Location Intelligence and Outdoor Location Intelligence). This is a reflection that geospatial and

location intelligence (GLI) solutions have become specialized by location accuracy, user role (business versus GIS expert) and use cases.

- **Mobile App Analytics** was dropped as the market for web and mobile analytics has converged, and the most basic user behavior tracking capabilities are found across all web analytics vendor products.
- **Mobile BI** was dropped as an innovation as it has moved past the Plateau of Productivity and is now considered a standard capability of nearly all analytics and BI platforms.
- **Open Data** was dropped as public datasets are increasingly available and supported directly from ABI platform providers and data catalog providers.
- **Real-Time Analytics** was dropped as the innovation has become widely implemented and moved off the Plateau of Productivity.

On the Rise

Immersive Analytics

Analysis By: Marty Resnick

Definition: Immersive analytics provides an engaging, collaborative and 3D visual interface for data analysis to serve new analytics use cases using augmented reality (AR), mixed reality (MR), and virtual reality (VR) technologies and techniques.

Position and Adoption Speed Justification: Organizations are at the early experimentation and proof of concept (POC) stage with immersive analytics. Early indications from both vendors and users are promising, and they point to the expansion of valuable use cases. We expect experimentation with POCs to continue for the next couple of years. Deployments are likely in the next two to five years.

Immersive analytics is at an early stage, with only a few vendors beginning to productize solutions, but this space is growing. Some vendors of analytics and business intelligence platforms are investigating how to build immersive analytics capabilities into their platforms, and most provide the architecture needed to supply data to immersive analytics environments. In addition to lab prototypes, 3D visualizations and immersive experiences are being developed by third-party developers, such as digital agencies.

Immersive analytics has a wide range of potential uses. For data scientists and data analysts, it could power 3D data exploration of complex n-dimensional data via VR. For operational managers, the ability to overlay information on physical objects, via AR, could enable direct and immediate delivery of analytics in a working context. In collaborative environments, such as the boardroom, immersive analytics could, via MR, shift management culture toward more data-centric decision making by enabling users to interact collaboratively with 3D analytics models while maintaining a presence in the physical world.

User Advice: Data and analytics leaders looking for innovative ways to explore data and make decisions should:

- Use a combination of augmented and immersive analytics to mitigate limited views of data.
- Review the roadmaps and capabilities of their existing analytics vendors and of those they may use in the future. As this field is still in its infancy, it's worth investigating new vendors in this sector.
- Identify use cases for specific immersive visualizations.
- Use immersive analytics as part of larger data storytelling through multiexperience initiatives, providing users the data they need, wherever they are, at the point of decision.

Business Impact: Immersive analytics could prove invaluable for organizations focused on data and analytics, which are critical for operational efficiency, automation, advanced decision making, monetization and revenue generation. The amounts of data that accompany these types of use cases, as well as relationship-based analytics, are huge. They are too vast for humans to comprehend, let alone act on, using data visualization delivery methods based on 2D screens. Immersive analytics could prove ideal for organizations implementing Internet of Things initiatives, given the massive amount of sensor data involved.

Benefit Rating: Transformational

Market Penetration: Less than 1% of target audience

Maturity: Embryonic

Sample Vendors: 3Data; IBM; Microsoft; Slanted Theory; Virtualitics

Recommended Reading: "Examine 4 Use Cases for Augmented Reality Apps in the Enterprise"

"3 Immersive Experience Use Cases That Provide Attractive Market Opportunities"

"Virtual Reality and Augmented Reality: Using Immersive Technologies for Digital Transformation, Customer Experience and Innovation"

Analytics Catalog

Analysis By: James Richardson; Rita Sallam

Definition: Analytics catalogs combine portal-like capabilities with curation and collaboration functions and applies them to analytics and BI content. This enables users to share, find, search, comment, and rate dashboards, reports and datasets from a diverse range of platforms in one place. They also help those managing portfolios of A&BI platforms to monitor, manage and migrate usage across technologies.

Position and Adoption Speed Justification: Many (perhaps the majority of) organizations use multiple A&BI technologies either to support a wide range of analytic processes, because of historic vendor relationships, or because of the best-of-breed preference. That situation is already commonplace and portfolio deployments are likely to grow. As such there is a need to help decision makers get to the right content from more than one underlying technology. Analytics catalogs address a real pain point impacting organizations using multiple analytics and BI tools by giving business users a single point of access. A number of these products go beyond simply surfacing content at the report or dashboard level, decomposing content down to individual charts or tables and maintaining full interactivity (via sorting, filtering, revisualization for example).

Managing access to multiple A&BI platforms is not a new problem. Historically organizations have built their own custom access points using standard intranet portal tools (commonly Microsoft SharePoint). However, that can be costly to do and requires ongoing maintenance, to the extent that Gartner has spoken to customers that have abandoned this build-it-yourself approach. Analytics catalogs productize that requirement into a COTS application.

There is little hype around these tools, but a clear need for them in many organizations. One reference customer Gartner interviewed said they were surprised that there were not more analytics catalogs in the market, and that they were so little known or used. Part of the answer to that may lie in the fact that vendors of A&BI platforms would rather their customers did not use competing products and so don't offer this functionality. The exception here is SAP Analytics Hub. SAP's entry into the space has brought some more attention, but analytics catalogs remain relatively not hyped, unlike data catalogs (see "Data Catalogs Are the New Black in Data Management and Analytics"). The relationship between these two forms of catalog is likely to develop quickly and they may converge. It could be argued that curating data is subset of a wider requirement that comprises managing an inventory of data assets and a range of analytic artefacts including those created by data science activities, not just those from A&BI platforms.

User Advice: Data and analytics leaders should:

- Explore the benefit that a managed single access point for analytics & BI content could provide to users.
- Compare the functionality and cost of any custom-built BI portals vs. that offered by commercial analytics catalog tools.
- Evaluate how these tools could help them to manage the life cycle of tools in their A&BI tool portfolio, particularly when it comes time to retiring older content or products and smoothing the user experience through transition.

Business Impact: There is little point in having reports, dashboards, data visualizations or datasets if end users cannot find them, or struggle to navigate them.

Anything that helps drive wider adoption of A&BI tools will help organizations become more data-centric. Analytics catalogs provide the opportunity to deliver a one-stop shop, and like online retailer stores, give internal users the chance to find content, and rank and review its relevance and business value.

Analytics catalogs are an enabling technology that can help businesses better operationalize and scale their analytics initiatives by providing metrics on usage and adoption across the full range of A&BI technology used.

Benefit Rating: Moderate

Market Penetration: 1% to 5% of target audience

Maturity: Adolescent

Sample Vendors: Metric Insights; Motio; SAP; ZENOPTICS

Recommended Reading: "Less Is More: Streamlining Your Analytics and BI Tool Portfolio"

Data Literacy

Analysis By: Valerie Logan; Alan D. Duncan; Sally Parker

Definition: Gartner defines data literacy as the ability to read, write and communicate data in context, with an understanding of the data sources and constructs, analytical methods and techniques applied, and the ability to describe the use-case application and resulting value.

Position and Adoption Speed Justification: A major inhibitor of the measurement, management and monetization of information assets is that creators and consumers of data and analytics capabilities face a language barrier. Due to ineffective communication, a lack of analytical and critical-thinking skills and limitations of organizational culture, they often struggle to make a business more "data-driven" because they do not "speak data" consistently. Respondents to Gartner's third and fourth annual Chief Data Officer Surveys ranked "poor data literacy" among the top-three internal roadblocks to success. They also identified cultural issues and a lack of talent and skills as major impediments to business growth.

Data literacy is a core enabler of digital business — alongside people, processes and technologies. Data literacy should be viewed as a central pillar of broader digital dexterity or digital workforce transformation efforts. Awareness of the data literacy challenge is increasing, with a growing number of organizations planning and delivering specific data literacy programs. However, as yet, only a few providers of data literacy assessments and training have emerged. The lack of common models/frameworks and localized training approaches are major obstacles in the way of rapid and widespread adoption. Additionally, the lack of comprehensive data literacy programs, standards, training and certification inhibits awareness and adoption.

User Advice: Increased demand for "data-driven" business and growing awareness of the need for data literacy and deliberate competency development are prompting leading organizations to pilot data literacy initiatives by, among other things, working with emerging providers of data literacy offerings. Given the limited number of providers, data and analytics leaders should begin data literacy workshop and training pilots of their own, which should include examples of the use of data storytelling and decision models to convert conversations into business-oriented dialogue. Despite the small number of providers in the market at present, offerings are developing rapidly as consulting services, providers of self-service and citizen data scientist software tools, and boutique firms emerge to address the demand within the next 18 months. Universities will also rapidly expand relevant courses to fill the talent gap. The general rate of adoption will be measured in years, though, much as Six Sigma that took years to achieve widespread adoption, and we expect data literacy to move only slowly along the Hype Cycle.

Pilot any of the following to get started:

- Data storytelling, to employ more narrative, visual formats and outcome-oriented emphasis.
- Decision modeling, to shift the conversation from self-service tools and dashboards to related decisions and actions.
- Outcome-driven data and analytics initiatives, to shift the conversation from data and analytics capabilities to the organizational outcomes that they help deliver.

Data and analytics leaders should explicitly champion data literacy. Partner with company's executives who "get it" and care about data literacy, data-driven culture and data monetization. Champion data literacy, data-driven culture and infonomics concepts with senior management to drive investment in relevant employee awareness and education programs. Use the people and organization dimensions of Gartner's IT Score model for data and analytics to provide context for data literacy efforts within your organization and work with human resources to develop a pilot data literacy training program. Strive to tie measurable business objectives to improved data literacy and to employee development and appraisal programs.

Services firms, software providers and others should align existing training and self-service enablement efforts with a broader curriculum and portfolio of data literacy offerings to meet the data literacy needs of both consumers and creators of data-driven solutions.

Business Impact: Developing data literacy is an imperative for any organization desiring to derive value from data. It is required across all industries, business domains and geographies, and will benefit any business process, role and decision where there is the opportunity to measure, manage and monetize data. Similar to the maturation of Six Sigma in the 1990s as a core competence, data literacy will impact all employees, from the board room to the break room, by becoming not just a business skill but a critical life skill.

Creators and producers of data, analytics and artificial-intelligence-based solutions will benefit from:

- A clear business context for analytics. This will help them understand how to ask a good question and apply critical thinking.
- A shared understanding of data sources, data quality and data elements across data types.
- An appropriate degree of understanding of the array of analytical methods available for measuring, monitoring and analyzing datasets in order to derive insight, and inform decisions and actions.

Data literacy can be framed as an important component of a broader workforce digital dexterity campaign, to help employees boost their ambition and ability to use data and technology in pursuit of better business outcomes.

Benefit Rating: High

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Sample Vendors: Accenture; Ambient Intelligence; AVADO; Cognizant; Data to the People; Experian; Pluralsight; Qlik; Tableau; Tuva

Recommended Reading: "Information as a Second Language: Enabling Data Literacy for Digital Society"

"Fostering Data Literacy and Information as a Second Language: A Gartner Trend Insight Report"

"Getting Started With Data Literacy and Information as a Second Language: A Gartner Trend Insight Report"

"Toolkit: Enabling Data Literacy and Information as a Second Language"

"How CDOs Engage With Their Stakeholders to Foster Data Literacy and Deliver Measurable Business Value"

"Artificial Intelligence Demands That CIOs Foster a Data-Literate Society"

"Data-Centric Facilitators Are Crucial for Enabling Data Literacy in Digital Business"

Conversational Chatbots for Analytics

Analysis By: Rita Sallam

Definition: Conversational chatbots analytics allows any user to ask voice or text questions of their data via a virtual personal assistant (VPA) or mobile device and receive back a natural language and, potentially, a visual analysis of the most statistically relevant and actionable insight for that user. It is the application of natural language processing (NLP) including natural language query and natural language generation/narration to a number of technologies including PDAs, mobile, bots, AI, augmented analytics, and analytics and BI.

Position and Adoption Speed Justification: As organizations transform into digital businesses, analytics becomes a critical enabler. Expanding access to insights from analytics to all workers will be key to driving transformative business impact. However, access to analytics content from BI and analytics and data science platforms has mostly been limited to power users, business analytics and specialist data scientists with varying degrees of analytical and technical skills. Gartner surveys show that only around 35% of employees have access to analytics and BI tools.

Conversational chatbots for analytics addresses this challenge by enabling any employee to interact with data to gain the most relevant, optimized and actionable insights for their role and context. For example, instead of logging into a dashboard, any user — from the C-suite to analysts to operational workers — can interact with virtual personal assistants, such as Amazon Alexa or Google Home, or their mobile phone via voice to ask for an analysis that is relevant to them. In combination with augmented analytics capabilities, sales manager might, for example, ask for an analysis of sales or pipeline or the system may have learned that the sale manager also looks at this information. Based on that person's role and/or behavior, he or she will be served up an explanation or narrative in text or voice of statistically important drivers of change and could be sent visualizations (via a device) that show important trends, patterns or outliers based on their role. Conversational chatbots for analytics will also be embedded in the workflow of applications that every employee uses.

Conversational chatbots for analytics applications are not available from most analytics, and BI vendors out of the box today and early integrations are immature. Qlik recently acquired chatbot vendor CrunchBot and now offers a product that integrates with Qlik Sense. Promising technology is available from Wolfram|Alpha (Enterprise), although the number of customer deployments is still limited. Most other analytics vendors are using APIs and building integrations through partnerships to make them easier to deploy. We expect these to become more out-of-the-box and enterprise-ready over the next two to five years.

User Advice: Data and analytics leaders should:

- Prototype current APIs to VPAs and bot engines to show the art of the possible to business stakeholders.
- Evaluate capabilities, roadmaps and partnerships of their analytics and BI platform vendors, as well as those from startups and other innovators.

- Assess solutions' maturity and scalability, particularly in terms of integration and ease of use, upfront setup/configuration requirements, language limitations, and types of analysis.

Business Impact: Conversational chatbots for analytics changes how users interact with data from what is currently mainly "drag and drop" elements onto a page, to more of a natural language processing that is supported by voice. This can dramatically improve the adoption of analytics by every employee rather than by predominant power users and business analysts, resulting in higher business impact.

People like to have at work what they have at home. This is a natural extension of integrating tech we use in our personal life into our work life.

As both a query mechanism and interpretation of results, conversational analytics represents the convergence of a number of technologies including VPAs, mobile, bots, AI, augmented analytics, and analytics and BI. For these reasons, there are a limited number of vendors which will provide a turnkey solution and, instead, conversational chatbots for analytics will mostly be an integration of technologies from multiple vendors in the near term.

Benefit Rating: High

Market Penetration: Less than 1% of target audience

Maturity: Emerging

Sample Vendors: Amazon; Qlik; Sisense; Unscrambl; Wolfram|Alpha (Enterprise)

Recommended Reading: "Augmented Analytics Is the Future of Data and Analytics"

"Top 10 Data and Analytics Technology Trends That Will Change Your Business"

"Magic Quadrant for Analytics and Business Intelligence Platforms"

"Magic Quadrant for Data Science and Machine Learning Platforms"

"How Citizen Data Science Can Maximize Self-Service Analytics and Extend Data Science"

"Pursue Citizen Data Science to Expand Analytics Use Cases"

Data for Good

Analysis By: Carlie Idoine; Lydia Clougherty Jones

Definition: "Data for good" is a movement in which people and organizations transcend organizational boundaries to use data to improve society. This data usage may be within an analytics and BI context or in more sophisticated data science and machine learning use cases, but the purpose is focused on social impact.

Position and Adoption Speed Justification: NGOs and public-sector organizations are trying to be more data driven, but they are challenged with a lack of knowledge, skills and expertise to leverage data to fulfill their missions. Meanwhile, commercial organizations have data that can be used for the good of society and have more data and analytics (D&A) expertise. By crossing traditional organizational boundaries, these stakeholders are uniting in their efforts to leverage data for the greater good and to provide more meaningful work to the most sought-after employees. Data for good requires that data not be held and managed within a single, commercial organization for its own specific (even those of public good) initiatives. It must be contributed to a larger community for use.

The number of organizations — from universities and communities to vendors — having a "data for good" focus has increased. For example:

- DataKind is a nonprofit organization that hosts data dives on behalf of charities and public-sector agencies. These dives involve data and analytics experts collaborating on datasets such as the effectiveness of blood drives, the opioid crisis and homelessness.
- Kaggle hosts online data science competitions with an added focus on "data science for good."
- Universities and community organizations such as the University of Chicago, the University of North Carolina, Bloomberg, and Sorenson Impact Center have annual "data for good" events.
- Analytic and BI vendors have special programs such as SAS's GatherIQ mobile app, which analyzes data around migrants, wildlife and sepsis.
- Data and analytics service providers (system integrators and consultancy companies) have established data for good initiatives, such as Slalom consulting for American Cancer Society or TCS for social transformation (pArIvartana). Six out of 19 service providers in the Magic Quadrant for D&A services have foundations or data for good programs.
- In terms of data, companies such as Google, Mastercard (Center for Inclusive Growth), and Yelp have made their data available for philanthropic and social causes.

Data for good is specifically advantageous for organizations that are both contributing the data and using it. At this time, such contributions are often considered altruistic and justifications for participating can be difficult to develop.

User Advice: Data and analytics leaders should:

- Leverage free resources (people/services, software, technology, data) from data and analytic vendors and organizations that support "data for good" projects.
- Participate in community events such as those hosted by DataKind, Kaggle, universities and other organizations to collaborate on "data for good" projects. This participation should include contributing to and exploring open-data initiatives.

- Establish “data for good” initiatives as part of social responsibility by allowing employees to spend so many hours a year on philanthropic initiatives. Use this HR benefit as a differentiator in recruiting and skills’ enhancement.
- Evaluate internal data to assess its usefulness for social purpose, while also adhering to privacy and security policies. Instill ethics and moral considerations in data use and sharing efforts.
- Grow awareness about “data for good.” Share internal and external case studies as well as resources from vendors and organizations that demonstrate not only what “data for good” is, but also the impact of such initiatives.

Business Impact: Lack of available analytic and data science skills continues to be a top concern for CIOs and chief data officers. This problem is potentially worse for nonprofit and government organizations to recruit and retain data and analytic workers in roles where the pay is often lower. The “data for good” movement gives public-sector organizations and NGOs a range of resources available in the form of free or reduced-cost technology, data, and skilled workers. Several data and analytic vendors offer the matching of volunteers with analytic initiatives for philanthropic causes.

In the commercial sector, offering a benefit to participate in “data for good” initiatives can be an evolution of philanthropic benefits that attract and retain workers in a tight labor market. As social impact investing is also on the rise, “data for good” initiatives can signal social responsibility to investors.

Benefit Rating: Moderate

Market Penetration: 1% to 5% of target audience

Maturity: Emerging

Sample Vendors: Alteryx; DataKind; Google; Qlik; Salesforce; SAS; Tableau; TCS; Teradata

Recommended Reading: “How to Use Data for Good to Impact Society”

“Magic Quadrant for Analytics and Business Intelligence Platforms”

“Magic Quadrant for Data and Analytics Service Providers, Worldwide”

Explainable AI

Analysis By: Saniye Alaybeyi

Definition: AI researchers define “Explainable AI” as an ensemble of methods that make black-box AI algorithms’ outputs sufficiently understandable. Gartner’s definition of explainable AI is broader — set of capabilities that describes a model, highlights its strengths and weaknesses, predicts its likely behavior, and identifies any potential biases. It can articulate the decisions of a descriptive, predictive or prescriptive model to enable accuracy, fairness, accountability, stability and transparency in algorithmic decision making.

Position and Adoption Speed Justification: Not every decision an AI model makes needs to be explained. There is considerable hype that is associated with explainable AI today. Although some vendors have introduced early explainable AI capabilities, most are using it for marketing purposes. Therefore, we decided to put explainable AI at prepeak on the Hype Cycle. Gartner anticipates that organizations do and will continue to achieve a lot of fantastic results without the need for full explainability. Depending on the business context, however, privacy, security, algorithmic transparency and digital ethics may demand different levels of requirements for explainability. For example:

- AI that makes decisions about people, such as rejecting a loan application, may require explainability. By law, providers of algorithms must give the user a reason for the rejection.
- According to the EU's GDPR, which took effect in May 2018, users affected by an algorithmic decision may ask for an explanation.
- AI that makes decisions in a closed loop with important consequences, such as autonomous driving, also has a high need for explainability due to ethical and possibly legal reasons.
- The Financial Stability Board (FSB) identified the lack of interpretability of AI and machine learning methods as "a potential macrolevel risk." The same board indicated that a pervasive use of these AI models that lack explainability may result in unintended consequences.
- Explainable AI comes up often during Gartner end-user client inquires, as well as in the news and media. During Gartner vendor briefings, vendors are also starting to claim they have explainable AI available to their customers. The Defense Advanced Research Projects Agency (DARPA) now projects that explainable AI will emerge in transportation, security, medicine, finance, legal and military applications.

User Advice:

- Foster ongoing conversations with various line-of-business leaders, including legal and compliance, to gain an understanding of the AI model's interpretability requirements, challenges and opportunities from each business unit. Integrate these findings into the development of the enterprise information management strategy.
- Build partnerships with IT, in particular with application leaders, to explain how the AI model fits within the overall design and operation of the business solution, and to give stakeholders visibility into training data.
- Start with using AI to augment rather than replace human decision making. Having humans make the ultimate decision avoids some complexity of explainable AI. Data biases may still be

questioned, but human-based decisions are likely to be more difficult to be challenged than machine-only decisions.

- Create data and algorithm policy review boards to track and perform periodic reviews of machine learning algorithms and data being used. Continue to explain AI outputs within changing security requirements, privacy needs, ethical values, societal expectations and cultural norms.

Business Impact: End-user organizations may be able to utilize some future interpretability capabilities from vendors to be able to explain their AI outputs. But eventually, AI explainability is the end-user organization's responsibility. End users know the business context their organizations operate in, so they are better-positioned to explain their AI's decisions and outputs in human-understandable ways. The need for explainable AI has implications for how IT leaders operate, such as consulting with the line of business, asking the right questions specific to the business domain, and identifying transparency requirements for data sources and algorithms. The overarching goal is that models need to conform to regulatory requirements and take into account any issues or constraints that the line of business has highlighted. New policies around the inputs and boundary conditions on the inputs into the AI subsystem, how anomalies are handled, how models are trained and the frequency of training need to be incorporated into AI governance frameworks. Many questions about the suitability of the AI model will rely on a clear understanding of the goals of the application(s) being designed.

Benefit Rating: High

Market Penetration: 1% to 5% of target audience

Maturity: Emerging

Sample Vendors: H2O.ai; IBM; Microsoft; simMachines

Recommended Reading: "Top 10 Data and Analytics Technology Trends That Will Change Your Business"

"Build Trust With Business Users by Moving Toward Explainable AI"

"Predicts 2019: Digital Ethics, Policy and Governance Are Key to Success With Artificial Intelligence"

At the Peak

Continuous Intelligence

Analysis By: W. Roy Schulte; Pieter den Hamer; Melissa Davis

Definition: Continuous intelligence is a design pattern in which real-time analytics are integrated into business operations, processing current and historical data to prescribe actions in response to business moments and other events. It provides decision automation or decision support. Continuous intelligence leverages multiple technologies such as augmented analytics, event stream processing, optimization, business rule management and machine learning.

Position and Adoption Speed Justification: The current hype is focused on holistic, integrated continuous intelligence solutions that share real-time information from multiple sources with multiple departments and applications to support multiple business functions. Examples include real-time 360-degree views of customers, supply chain networks and enterprise nervous systems in airlines, railroads and other transportation operations. Simpler kinds of continuous intelligence are already common in point systems such as mobile device navigation, monitoring the health of machines, contact center monitoring, pop-up web ads, high frequency trading and package tracking. The hardware and software technologies for holistic, integrated continuous intelligence, including inexpensive sensors, publish-and-subscribe messaging systems such as Apache Kafka, event stream processing platforms and augmented analytics, are available and affordable. However, many companies lack the skills necessary to develop their own custom-built solutions so holistic continuous intelligence will take five to 10 years to achieve 50% penetration of the target audience.

User Advice: Data and analytics leaders should consider continuous intelligence for new business processes and when making significant changes to existing processes. It applies to situations in which real-time data from the last few seconds or minutes significantly improves business decisions. It is not relevant where equally good decisions can be made with data that is hours, days, weeks or older. It goes beyond real-time descriptive, diagnostic and predictive analytics by supplying prescriptive information about the best available action to be taken in response to the situation. The potential role of continuous intelligence should be discussed with business managers and subject matter experts early in the requirements-gathering process. If continuous intelligence is implemented, it will fundamentally affect the design of business processes and their data and analytics. Companies can reduce the effort of achieving holistic continuous intelligence by subscribing to SaaS offerings, or acquiring packaged applications or devices that provide internal continuous intelligence on a point basis. However, holistic continuous intelligence will still entail custom design and integration with multiple applications, including independently owned and operated systems. This will require multidisciplinary collaboration among business domain experts, change managers, architects and developers. It may leverage messaging systems, event stream processing platforms, decision management tools, intelligent business process management suites (iBPMS), IoT platforms or other development, middleware and analytics products.

Business Impact: Continuous intelligence plays a major role in digital business transformation projects. A key benefit is improved situation awareness and a common operating picture across business functions by providing real-time dashboards and alerts. Equally important is the capability to trigger automated responses by sending signals to machines or initiating business processes in cases where the decision on what to do can be automated. Systems with continuous intelligence leverage real-time context data to support decisions for customer support, customer offers, risk, or allocating resources in the most efficient manner possible. However, enterprises that do not already have staff expertise in messaging, stream analytics, machine learning and decision management disciplines may need to hire outside service providers or train their staff on the new disciplines.

Benefit Rating: Transformational

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Sample Vendors: Confluent; FICO; RedPoint Global; SAS; Software AG; TIBCO Software; Unscrambl; Vitria; XMPro; ZineOne

Recommended Reading: "Make Your Customer Engagement Hub Real Time With Continuous Intelligence"

"How to Architect Continuous Intelligence Solutions"

"Innovation Insight for Continuous Intelligence"

"Building Your Continuous Intelligence Capability for Digital Transformation"

"How Companies Succeed at Decision Management"

"How to Move Analytics to Real Time"

Data Storytelling

Analysis By: James Richardson

Definition: Data storytelling combines interactive data visualization with narrative techniques to deliver insights in compelling, easily assimilated forms. Analytic data stories are intended to prompt discussion and drive collaborative decision making, while journalistic or reportage style data stories aim to inform or educate, often using infographics. Both commonly link data and time or events via a narrative story arc.

Position and Adoption Speed Justification: Data stories offer a compelling combination of capabilities that help people to better engage with data. Most analytics and BI platforms now include basic functionality to create and share data stories. These stories can take several forms, most frequently data-connected slideshows or storyboards, and annotated dashboards, and occasionally more graphic design style infographics. As the use of self-service analytics matures, users are beginning to use data storytelling tools and techniques to better communicate data findings to decision makers. However, although enabled by new functional capabilities, the outcome of data storytelling draws much more an emergent set of skills, practices and behaviors around how data is socialized and used in organizations. Today, most data stories are being told by analysts, but machine-driven data storytelling (via applied ML) is emerging, offering the promise of news-style headlines and narratives generated automatically and specifically for individuals. Data storytelling is part of a broader movement oriented around data literacy and explaining and expressing data and analytics in a business-friendly and relevant way.

User Advice: Data and analytics leaders should:

Evaluate and experiment with the data storytelling capabilities of analytics and business intelligence platforms. In particular, examine how their incumbent portfolio of technologies supports the creation of a storyboard style presentations with embedded analytical content.

Task members of their Analytic Community of Excellence (ACE) to investigate data storytelling as an extension to their use of interactive visual exploration and analytic dashboarding, in order to provide a richer delivery of information by adding narrative and context.

Prepare programs to develop and instill the particular mix of data visualization design, narration and presentation skills needed to support effective data storytelling. Identify a team of business analysts and citizen data scientists to act as a virtual team of data storytellers.

Appraise your organization's managerial and decision-making culture, and assess data literacy as an overall capability, by running pilot assessments and workshops in selected lines of business and identifying areas for targeted training and development.

Business Impact: Too many decision makers still overlook, ignore or avoid the data insights delivered to them. This can be a cultural issue; however, there is also a simpler factor at play, how data insights are delivered. In many cases, even where the insight does spark interest it may lack the context required to drive a decision. Data storytelling can help break down managerial inertia and apathy toward data by adding context and making it more accessible. The business impact of data findings delivered as a story can be much higher, as story is familiar to all. A data storytelling led approach can transform how analytics and data science teams work by getting them to focus on how their audience, often nontechnical decision makers, need data to be presented to them to be most compelling.

From an ROI perspective, the use of data storytelling functionality can help drive adoption of A&BI technology, by repositioning how these tools are used from simply visualizing data to becoming as the key medium for the effective communication of insights about data. This is important when Gartner research shows that adoption of A&BI platforms is still less than it should be to be of most impact.

Benefit Rating: High

Market Penetration: 1% to 5% of target audience

Maturity: Emerging

Sample Vendors: Information Builders; MicroStrategy; Qlik; Tableau Software; Toucan Toco; Workday (Stories.bi); Yellowfin

Recommended Reading: "Beyond BI Reporting: Engaging Decision Makers Through Data Storytelling"

"How to Use Storytelling to Sell Your Data Science Projects"

"How to Get More Value From Data Visualization"

"Information as a Second Language: Enabling Data Literacy for Digital Society"

Edge Analytics

Analysis By: Eric Hunter; W. Roy Schulte; Jim Hare

Definition: "Analytics" is the discipline that applies logic (i.e., "rules") and mathematics ("algorithms") to data to provide insights for making better decisions. "Edge" analytics means that the analytics are executed in distributed devices, servers or gateways located away from corporate data centers or cloud servers closer to where data from "things" (commonly sensors) is being generated.

Position and Adoption Speed Justification: Edge analytics moved further along the Hype Cycle toward the Peak of Inflated Expectations driven by increased expectations for edge analytics via machine learning and advances in the hybrid cloud. Five drivers for edge analytics use cases include latency/determinism, local interactivity, data/bandwidth considerations, privacy/security, or limited autonomy. Edge analytics offerings primarily support decentralized deployments of device-isolated insights. However, as connectivity advances and the demand for cross-device analytics increase, edge analytics will be tasked not only with providing edge-resident insights, but also to support conversion and compression to move data to hybrid cloud platforms for aggregation.

An increasing number of IoT platform and analytics vendors are adding the ability to deploy and run small-footprint analytics packages on edge devices — supporting both endpoints and aggregation devices like an IoT gateway. It reflects the shifting balance between edge and cloud computing. Public cloud providers are further accelerating this trend with announcements from Amazon Web Services (AWS Outposts), Microsoft (Azure Stack), Google (Anthos) and IBM (OpenShift). This trend is being driven by several factors including rightsizing connectivity to the edge, real-time analytics and data privacy considerations.

User Advice: Analytics leaders should consider edge analytics across the following five imperatives:

- **Limited Autonomy.** An individual device, asset or even a larger distributed site must provide analytic insights even in the midst of disconnection from cloud or data center infrastructure and resources

- **Privacy/Security.** Regulations or data privacy laws require that data be kept within the location of origin or the organization deems the transfer of data to introduce too many security vulnerabilities
- **Latency/Determinism.** Network connectivity does not have the ability to support desired latency or stability requirements
- **Local Interactivity.** Cross-device interdependencies as part of a larger system require edge-resident analytics
- **Data/Bandwidth.** It would cost too much to upload the full volume or fidelity of generated data, and there is no benefit to moving device-level data to a central location for aggregated analysis. Another scenario includes edge analytics for support of centralized cloud or data center analytic strategies by converting/compressing edge-generated data alongside for network transmission

Business Impact: Running analytics at the edge will become commonplace for both data and analytics and IoT architectures by the time it reaches the plateau.

Advantages include:

- **Faster response times.** Many sensors deliver digital and analog data at very low millisecond or sub millisecond intervals. When that data is sent to a central location for analysis, delays are introduced, and it loses its value for real-time requirements.
- **Reduced network bottlenecks.** Minimizes the risk of congesting device networks with full-fidelity or high-bandwidth data transmission (video, millisecond interval sensor reads and analog sensors).
- **Data filtering.** This reduces the data management and storage overhead by using edge analytics to look for just the actionable data. As a result, only the necessary data is analyzed or sent on for further analysis.
- **Reliability.** The remote location can remain in operation even if the network, cloud servers or data centers are unavailable.
- **Reduced communications cost.** Device-only edge analytics eliminate communication costs while edge device-based conversion and compression can dramatically lower costs versus sending raw analog or full-fidelity digital data to a central cloud or data center

Disadvantages include:

- **Increased complexity.** Remote, distributed analytics deployment and management make the deployment and management more complicated than for aggregated data in a single location — particularly when devices are heterogeneous in nature — lacking in standardization.

- **Reduced data granularity.** There is a potential loss of useful insight by discarding raw data stored locally as "data exhaust."
- **Lack of cross-device analytics.** Unless device data is transmitted to a consolidated location from the edge, leaders can lose the ability to deliver cross-device insights and analytics.
- **Device maintenance and technical currency.** Edge analytics will require more capable devices that increase demands for monitoring and maintenance of device health along with introducing demands for keeping devices up-to-date with both software and hardware revisions.

Benefit Rating: High

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Sample Vendors: Amazon Web Services; Arundo; Element; FogHorn; Iguazio; Microsoft Azure; Particle; PTC (ThingWorx); SAS; Sisense

Recommended Reading: "Top Strategic IoT Trends and Technologies Through 2023"

"Top 10 Strategic Technology Trends for 2019: Empowered Edge"

"The Edge Completes the Cloud: A Gartner Trend Insight Report"

"Deploying IoT Analytics, From Edge to Enterprise"

"4 Technology Sources for an AI-Enabled Enterprise"

"What Tech CEOs Must Know About Edge Computing in 2019"

Natural Language Generation

Analysis By: Rita Sallam

Definition: Natural language generation (NLG) automatically creates linguistically rich description of insights found in data. Within the analytics context, the narrative changes dynamically as the user interacts with data to explain key findings or the meaning of a chart or dashboard. NLG combines natural language processing with machine learning and artificial intelligence to dynamically identify the most relevant insights and context in data (trends, relationships, correlations).

Position and Adoption Speed Justification: Whereas text analytics focuses on deriving analytic insights from textual data, NLG is used to synthesize textual content by combining analytic output with dynamic selection-driven descriptions.

Although still in the early stages of adoption, NLG is being used effectively to reduce the time and cost of conducting repeatable analysis. Examples include, operational and regulatory reporting, earnings reports in the financial services sector, benefits statements and weather forecasts in the government sector, and personalized messages in the advertising sector. It is also used for data products such as sports analytics (personalized "fantasy football" analysis and reports), customer communications, and marketing and research information services.

The combination of NLG with modern analytics and business intelligence (BI) — used to create analytics content including analytics applications — is one of the most promising applications improving insights derived from analytics for all users.

With the addition of NLG, augmented analytics platforms — for example, those of Salesforce (Einstein Analytics) and search/natural-language-query-based platforms such as ThoughtSpot and AnswerRocket — can automatically generate a written or spoken context-based narrative of findings in the data. SAS is leveraging its own NLG technology to offer this capability as part of SAS Visual Analytics. This accompanies visualization, storyboard and batch reports to fully inform the user about what is most important and actionable. Analytics and BI teams can now also integrate stand-alone NLG engines (such as those of Automated Insights, Narrative Science and Yseop) with modern analytics and BI or data science platforms to explain findings from analytics to information consumers and citizen data scientists. Narrative Science, Automated Insights, and Yseop all now offer APIs for their platforms. Integration of NLG with analytics and BI platforms and virtual personal assistants — such as Amazon Alexa, Apple Siri, or Google Assistant for conversational analytics — will further drive adoption.

Easy configuration and multilanguage support will be necessary for broad adoption. We expect that, due to NLG's potentially beneficial impact to expand analytics to a broader audience, NLG will be a feature of most modern analytics and BI platforms by 2020. We already see this happening, with most modern analytics and BI vendors offering or planning to offer NLG through integration with third-party NLG vendors or organic development with varying degrees of automation and control of story tone, style and verbosity.

User Advice: Data and analytics leaders should:

- Integrate NLG with existing modern analytics and BI and data science initiatives, or explore emerging augmented analytics tools that embed NLG.
- Assess their organization's readiness for business-user-accessible advanced analytics in terms of alignment with business outcomes.
- Monitor the NLG capabilities and roadmaps of their analytics and BI and data science platforms, as well as of startups.
- Be aware of a solution's maturity, particularly in terms of data integration and preparation requirements, the platform's self-learning capabilities, upfront set-up and configuration required,

the range of languages supported, the extent of narration for a single chart or across a dashboard, the degree of story automation and control supported and the accuracy of the findings and narration.

- Understand potential drawbacks relating to multilingual user scenarios, as NLG requires specific libraries for each language in use. Additionally, industry-specific use cases need to be considered carefully with respect to jargon, tone and specialized ontologies.
- Recognize that NLG could be attractive to government organizations that are required to have their analytics and BI solutions comply with the Americans with Disabilities Act (in the U.S.), and similar mandates in other countries.

Business Impact: NLG supports a number of productivity-enhancing use cases that reduce the need for writers (such as of financial reports, sports analysis or product recommendations) outside analytics.

The combination of NLG with automated pattern/insight detection and self-service data preparation has the potential to drive the user experience of next-generation augmented analytics platforms. It could also expand the benefits of advanced analytics to a wider audience of business users and citizen data scientists and makes existing analysts and data scientists more efficient.

Many users have varying degrees of analytics skill to correctly interpret and act on statistically significant relationships in visualization. NLG has the potential to assist with consistent interpretation of insights.

Context-based narration will reinforce mobile BI use cases, where a lack of screen space is a major impediment to information consumption. It will also expand the use of conversational analytics that combine NLQ, chatbots and NLG via virtual personal assistants. Moreover, it will reduce the time and cost involved in creating regular operational and regulatory batch reports.

Benefit Rating: High

Market Penetration: 1% to 5% of target audience

Maturity: Emerging

Sample Vendors: AnswerRocket; Arria NLG; Automated Insights; Marlabs; Narrative Science; Salesforce (Einstein Analytics); SAS (Visual Analytics); ThoughtSpot; Yseop

Recommended Reading: "Magic Quadrant for Analytics and Business Intelligence Platforms"

"Top 10 Data and Analytics Technology Trends That Will Change Your Business"

"Cool Vendors in Analytics"

"Critical Capabilities for Analytics and Business Intelligence Platforms"

Decision Management

Analysis By: W. Roy Schulte; Erick Brethenoux; Pieter den Hamer

Definition: Decision management is the discipline of designing, building and maintaining systems that produce structured decisions. In this context, a “decision” is a judgment, conclusion or determination of what to do. A decision is structured if it can be documented in an explicit decision model, which is a representation of the decision-making process including data inputs, algorithms and results. Decision making that is invoked by other applications uses prescriptive analytics such as optimization, business rules and machine learning.

Position and Adoption Speed Justification: Companies are ramping up their use of decision management to cope with the increasing demand for decision automation, and the growing complexity of decisions in business. Design approaches have evolved to focus first on requirements and decision models before developing analytics or business rules. Business rule management systems (BRMSs) are evolving into decision management suites to support decision modeling, machine learning (ML) and optimization.

Recent advancements include:

- Knowledge graph representations at scale
- Agent-based decision intelligence techniques
- Augmented analytics
- Formal standards for decision modeling (such as Object Management Group’s Decision Model and Notation (DMN))

Many IT leaders, including data and analytics leaders, have limited understanding of the available techniques and tools, or their value. Many applications that could benefit from decision management do not use it yet, and it will take more than five years to reach the Plateau of Productivity.

User Advice: Decision management typically applies to continuous intelligence and other operational decisions, but it is also relevant to some strategic and tactical decisions. Decision-making software solutions may be discrete applications, but are more often subsystems, such as callable decision services or embedded code segments that are component parts invoked by larger applications.

Data and analytics leaders should:

- Use decision management for complex or repeatable decisions that involve substantial calculations, frequently changing logic, or traceable decision making.

- Use decision management for decision automation for decisions that can be fully specified in a model and implemented in software with no need for direct human involvement at decision time.
- Use decision management for decision support for decisions that require both analytics and human judgment.
- Develop a basic understanding of business rule processing (decision tables, for example), ML, optimization and other prescriptive analytics to guide the selection of software.
- Use data brokers and other sources of context data to obtain the information needed for more accurate and more precise decisions.
- Improve complicated decisions that involve tradeoffs among alternative courses of action by using *decision-problem* models (those based on management science), which calculate outcomes from different inputs.
- Improve repeatable decisions that are primarily based on policies, heuristics or ML by using *decision-composition* models that document the act of decision making, and by exploring new explainable AI techniques.

Business Impact: Decision management improves the design and software engineering process for systems that use prescriptive analytics by focusing attention on the business goals, requirements, decisions and subdecisions before jumping into detailed analytics and rules. Early use of decision management was concentrated in insurance and loan underwriting, mortgage approval, resource allocation, logistics, and public-sector applications, such as approving permits and determining welfare and taxes. More recently, it spread into other data- and logic-intensive applications, particularly customer experience management, compliance, fraud detection and risk management.

Decision management:

- Strengthens collaboration among business leaders, subject matter experts, business analysts, management scientists, data scientists and software developers.
- Makes it easier to develop sophisticated decision-making systems that combine rules, ML and optimization techniques.
- Helps make decisions more accurate, consistent, transparent and auditable.
- Supports continuous decision improvement.
- Improves compliance with corporate and legal requirements.

- Facilitates sharing business policies and rules among departments and external business partners.

Benefit Rating: High

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Sample Vendors: Actico; Decision Management Solutions; Enova Decisions; Experian; FICO; IBM; Red Hat; Sapiens International; SAS; Signavio

Recommended Reading: "How Companies Succeed at Decision Management"

"Decision Intelligence Is the Near Future of Decision Making: A Gartner Trend Insight Report"

"Develop Good Decision Models to Succeed at Decision Management"

"Innovation Insight for Optimization"

"Innovation Tech Insight for Business Rules Management Systems"

Augmented Analytics

Analysis By: Rita Sallam; Carlie Idoine

Definition: Augmented analytics uses machine learning to automate data preparation, insight discovery, data science, and machine learning model development and insight sharing for a broad range of business users, operational workers and citizen data scientists. It is expanding insights by using AI and ML techniques to deliver analytics to everyone in the organization with less time, skill and interpretation bias of current manual approaches.

Position and Adoption Speed Justification: Visual-based data discovery — a key feature of current modern analytics and business intelligence BI platforms — has been transformative in the way it enables business users to generate analytics insights (in comparison with traditional BI technologies). However, many of the activities associated with preparing data, finding patterns in data building data science and machine learning models on complex combinations of data, and sharing insights with others, remain highly manual. As a result, it is not possible for users to explore every possible pattern combination, let alone determine whether their findings are the most relevant, significant and actionable.

Relying on business users to find patterns manually may result in users exploring their own biased hypotheses, missing key findings and drawing their own incorrect or incomplete conclusions, which may adversely affect decisions and outcomes.

Augmented analytics includes:

- Augmented data preparation, which uses machine learning automation to augment data profiling and data quality, harmonization, modeling, manipulation, enrichment, metadata development and cataloging.
- Augmented analytics in analytics and BI platforms, which is a key feature of next-generation modern analytics and BI platforms. It enables business users and citizen data scientists to automatically find, visualize and narrate relevant findings, such as correlations, exceptions, clusters, segments, outliers, predictions, and prescriptions without having to build models or write algorithms. Users explore data via visualizations, search and natural language query technologies, supported by natural-language-generated narration interpretation of results.
- Augmented data science and machine learning, which automates key aspects of advanced analytic modeling, such as feature and model selection. Some platforms offer model explanation and will automate aspects of model management. This reduces the requirement for specialized skills to generate, operationalize and manage an advanced analytics model.

Augmented analytics capabilities will advance rapidly along the Hype Cycle to mainstream adoption, as a key feature of data preparation, modern analytics and BI and data science platforms. More importantly, automated insights from augmented analytics will also be embedded in enterprise applications — for example, those of the HR, finance, sales, marketing, customer service, procurement and asset management departments — to optimize the decisions and actions of all employees within their context, not just those of analysts and data scientists.

Augmented analytics will also be a key feature of conversational chatbots for analytics. This is an emerging paradigm that enables business people to generate queries, explore data, and receive and act on insights in natural language (voice or text) via mobile devices and personal assistants.

User Advice: Data and analytics leaders should:

- Embrace augmented analytics as part of a digital transformation strategy to deliver more advanced insights to a broader range of users — including citizen data scientists and, ultimately, operational workers — without expanding the use of data scientists. Pilot to prove the value and build trust.
- Monitor the augmented analytics capabilities and roadmaps of modern analytics and BI, data science platforms, data preparation platforms, and of startups as they mature. They should do so particularly in terms of the upfront setup and data preparation required, the types of data that can be analyzed, the types and range of algorithms supported, languages supported, integration with existing tools, explainability of models, and the accuracy of the findings.
- Explore opportunities to use augmented analytics to complement existing modern analytics and BI, data science initiatives and embedded analytic applications, where automating algorithms to detect patterns in data could reduce the exploration phase of analysis and improve highly skilled data science productivity.

- Recognize that citizen data scientists must collaborate with, and be coached by, specialist data scientists that still need to validate models, findings and applications.

Business Impact: Expanded use of machine learning automated and human-augmented models will translate into less error from bias, which is inherent in manual exploration processes. It will reduce the time users spend on exploring data, while giving them more time to act on the most relevant insights from data. It will also give front-line workers access to more contextualized analytical insights and guided recommendations to improve decision-making and actions.

Gartner predicts that, by 2020, due in large part to the automation of data science tasks, citizen data scientists will surpass data scientists in the amount of advanced analysis produced. This growth, enabled by augmented analytics, will complement and extend existing modern analytics and BI and data science platforms, as well as enterprise applications, by putting insights from advanced analytics — once available only to data science specialists — into the hands of a broad range of business analysts, decision makers and operational workers across the enterprise, driving new sources of business value.

Benefit Rating: Transformational

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Sample Vendors: DataRobot; Outlier; Paxata; Prevedere; Salesforce (Einstein Analytics); SparkBeyond; Tellius; ThoughtSpot; Trifacta

Recommended Reading: “Magic Quadrant for Analytics and Business Intelligence Platforms”

“Magic Quadrant for Data Science and Machine Learning Platforms”

“How Citizen Data Science Can Maximize Self-Service Analytics and Extend Data Science”

“Pursue Citizen Data Science to Expand Analytics Use Cases”

“Augmented Analytics Is the Future of Data and Analytics”

“Top 10 Data and Analytics Technology Trends That Will Change Your Business”

BI Search/Natural Language Query

Analysis By: Rita Sallam

Definition: Search-based BI and natural language query (NLQ) allow business users to query data and enterprise systems using business terms typed into a search box or via voice. Vendors may use different techniques. Some use keyword search, and others translate search terms into natural language questions using natural language processing (NLP) technology. Some use a combination of both.

Position and Adoption Speed Justification: Gartner estimates that adoption of analytics and business intelligence (BI) tools is still hovering at around 35% of employees in organizations. Despite significant advances in the usability of the current point-and-click visual-based modern analytics and BI platforms, this paradigm is still too hard for most business users to ask their own questions.

Historically, vendors have made multiple attempts to bring search and/or NLQ into the analytics and BI context, but they were not well-adopted for a variety of reasons. In some cases, the indexed datasets were limited, the costs were too high, or the language interpretations were too inaccurate.

However, interest in such tools is growing, with new entrants and new features within existing platforms addressing many of these challenges.

Currently, vendors take a wide range of approaches to enable such interfaces. Some use simple keyword matching (the familiar Google-style “search”). Others use robust natural language queries with support for more-sophisticated queries using industry-specific language. Early efforts, for example, may allow a user to ask for “sales by product” that generates a basic bar chart. More robust capabilities would support questions such as, “show me top-selling products within a 50-mile radius and comparing this year with last year.” Although “top selling” is not a keyword, the platform understands that it must apply a rank function, perform geographic analytics, and then do a subquery to compare year over year.

Vendors such as ThoughtSpot, AnswerRocket and Tellius have been early to the market with offerings that combine NLQ with interactive visualization and automated pattern exploration (augmented analytics) and explanation of findings via natural language generation (NLG) for what will ultimately be a conversational experience. Some like Qlik (through acquisition), Sisense and others through partner integrations have extended this experience with early integrations with chatbots. Most analytics and BI platforms either have early products and/or are aggressively investing in NLP (NLQ — the focus of this IP, NLG and chatbot integration) as a key part of their roadmaps. Others like EasyAsk access the metadata of analytics and BI platforms and can provide a single NLQ interface into multiple analytics and BI platforms.

Platforms such as Attivio or Sinequa enable users with minimal training to find relationships across structured and unstructured data (including transactions, email correspondence, social media chatter, survey data, call center records and relationships). These vendors often also apply machine learning and AI techniques as well as advanced content analytics such as text, social and sentiment analytics. These tools often also have SQL APIs for broad user accessibility and use with existing analytics and BI tools.

Search/NLQ is becoming an increasingly important interface for analytics and BI content creation, analysis, exploration, augmented analytics and conversational analytics to extend access to analytics to mainstream business users. As demand for pervasive analytics increases and analytics and BI platform vendors respond by improving their support for and innovation around search/NLQ, NLQ will rapidly become a standard and critical capability of analytics and BI platforms rather than a specialty point solution.

User Advice: Analytics leaders looking to make analytics more pervasive might consider using search and NLQ to help workers not accustomed to traditional, structured BI tools find the insights and information they need to make decisions.

Overtime, BI search/NLQ may be a less differentiated feature, but some vendors also may have strengths in supporting more complex questions and analytics as well as terminology related to particular verticals.

Organizations should assess vendor differences in the types and complexity of questions that can be asked, data scale, data types supported, as well as integration with augmented analytics, NLG and chatbots.

They should assess how NLQ will fit into their business analytics solution architecture and, more widely, how it relates to their enterprise search tools (what Gartner now calls Insight Engines).

In general, IT must be a key part of the evaluation and adoption of search-based NLQ specific vendors and capabilities. These tools often require some level of IT support for deployment, data ingestion, integration/modeling and application development.

Business Impact: Search/NLQ capabilities can help drive adoption by users resistant to, or intimidated by, using traditional BI interfaces for interacting with data, but who are quite comfortable using a search engine to find the information they need. Moreover, search/NLQ vendors that support queries across both structured and unstructured data can unify fact and context, thereby enabling users to explore the “what” and the “why” of data in one step.

Benefit Rating: High

Market Penetration: 1% to 5% of target audience

Maturity: Adolescent

Sample Vendors: AnswerRocket; Attivio; EasyAsk; Information Builders; Microsoft; Oracle; SAP; Sinequa; Tableau; ThoughtSpot

Recommended Reading: “Magic Quadrant for Analytics and Business Intelligence Platforms”

“Predicts 2019: Analytics and BI Strategy”

“Cool Vendors in Analytics”

“Top 10 Data and Analytics Technology Trends That Will Change Your Business”

Digital Ethics

Analysis By: Jim Hare; Frank Buytendijk; Lydia Clougherty Jones

Definition: Digital ethics comprises the systems of values and moral principles for the conduct of electronic interactions, and the use and sharing of data between people, businesses, governments and things.

Position and Adoption Speed Justification: Digital ethics jumped several positions toward the Peak of Inflated Expectations due to the recent wake of well-publicized negative press, rising public discourse, and new regulatory compliance including data privacy considerations. Current themes such as "artificial intelligence," "fake news," and "digital society" are triggers driving the increased need for digital ethics. Innovations such as the Internet of Things, 3D printing, cloud, mobile, social and AI are moving faster than business, governments and society can organize around it or even comprehend. Government commissions and industry consortiums are actively developing guidelines for ethical use of AI (see "Ethics Guidelines for Trustworthy AI").

The probability that unintended consequences will occur is high as the use of technology creates distance between morals and actions. For business and the technologies used in business, a morally agnostic stance is a position that simply cannot and should not be sustained. Digital ethics require societal, economic, political and strategic debate, new types of governance, and new processes and technologies to control new technologies.

User Advice: Privacy rules and data protection provide a legal minimum in handling data that is insufficient. Instead, take a "care ethics" approach to the application of digital technologies in the business world to reconcile principles and consequences. The core question of care ethics is, "How do we take responsibility for the consequences of our actions, even if they are unintended?" (see "Data Ethics Enables Business Value"). In the digital world, the concept of care ethics is not only about people, but also about how businesses and even technologies act. Care ethics teaches that ethics is about taking responsibility when confronted with situations you feel are not OK. Apply "care" ethics by following these call to actions:

- Be empathetic — put yourself in the other person's shoes; develop a sense of right and wrong that goes past just being afraid of punishment or hoping to generate a product sale whether legally or in terms of customer loyalty.
- Take responsibility — taking responsibility is essential for taking the lead within your ecosystem, and being the interface to the customer or citizen. In emerging digital environments, taking responsibility over the use of digital technologies, even if legally not required, builds and improves trust.
- Display competence — build the capacity and expertise to be able to quickly and adequately address problems. Don't simply acknowledge the need to care and accept the responsibility; you also need to be able to follow through.

- Promote trust — trust is needed to make the other three calls to action work. It is great to take responsibility, but if your stakeholders do not trust you to do so, your offer will not be accepted.

Business Impact: Digital ethics should be treated as a tangible business practices discipline rather than an academic discussion. Key areas where it should be applied include social and mobile technologies, and social interaction; cloud and security; big data and privacy; autonomous technologies and freedom; artificial intelligence/robotization and the value of work; and predictive algorithms and decision-making.

The four areas of business impact, listed in increasing order of "moral development" are:

- **Submitting to compliance —** staying within the boundaries of the law.
- **Mitigating risk —** being mindful of not using technology in ways that can upset stakeholders, or cause reputational or financial risk in other ways.
- **Making a difference —** making ethical use of data and technology as a proposition that sets you apart in the market. For example, this could be in terms of data for good initiatives or social purpose.
- **Follow your values** — there is a direct correlation between the use of technology and delivering value to customers, other stakeholders and yourself.

Actively engage and participate in online data ethics and data for good initiatives such as Data for Good (see "How to Use Data for Good to Impact Society").

Benefit Rating: High

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Recommended Reading: "Top 10 Strategic Technology Trends for 2019: Digital Ethics and Privacy"

"Digital Ethics, or How to Not Mess Up With Technology, 2017"

"How to Use Data for Good to Impact Society"

"The CIO's Guide to Digital Ethics: Leading Your Enterprise in a Digital Society"

"How to Apply Gartner's Digital Humanism Manifesto"

"Data Ethics Enables Business Value"

"Modernize Data Privacy to Put the Personal Back Into Personalization"

"Workplace Analytics Needs Digital Ethics"

"The #DigitalSociety Requires a Digital Social Contract"

Data Catalog

Analysis By: Guido De Simoni; Ehtisham Zaidi

Definition: A data catalog is a technology capability that is used to manage an inventory of heterogeneous and distributed data assets through the discovery, organization and description of the enterprise datasets. It provides context to help data analysts, data engineers, data scientists, data stewards and other data consumers to locate a relevant dataset and understand what it means, in order to determine and extract business value from it.

Position and Adoption Speed Justification: While a data catalog continues to be viewed as a critical capability in broader data management and analytics solutions, point catalogs (that are offered as part of a broader data management, cloud or analytics solution) will be successful in accessing and inventorying metadata only within the context of these narrow or use case specific solutions. Just like the market ended up introducing data silos, there is a growing fear of introducing metadata silos due to these embedded data catalogs in broader solutions. The market is therefore looking for independent/stand-alone catalogs that are application neutral and more capable of cataloging data across the organizations data assets. Gartner also believes that there is still room for specialized data catalogs that are more mature in their usage of machine learning to automate parts of the data catalog implementation process. Therefore, while we do believe that many data and analytics offerings will increasingly include data cataloging as an included capability, within their specific tools, there appears to be an emerging case for stand-alone data catalogs. However best-of-breed, stand-alone catalogs will become less relevant over time since the real value is not in cataloging but in what you do with the results — as in the use case. In the longer term the data catalog will be an AI-automated feature. As technology capability is still valid to state that data catalog will be obsolete before plateau.

User Advice: The overall complexity and sophistication of the business data environment — along with the number of datasets, their volumes and distributed nature — are rapidly overwhelming human analysts; particularly with the increasing need to incorporate and correlate exogenous datasets in support of innovative use cases driven by digital business and the IoT.

- Data and analytics leaders should exploit this emerging category of tools or solutions that embed data catalogs as a capability or as a stand-alone offering and that are present in the market under a variety of different names.

- Evaluate each solution alongside your existing data investment because different vendors have subtly different approaches to addressing data catalogs and no one catalog will yet meet all your data and analytics needs.

- Your functionality requirements should be balanced with other aspects such as vendor execution and vision, service and support, requirements for information security, data and analytics governance and total cost of ownership.
- Proceed in the knowledge that tool-specific embedded data catalogs (such as those delivered as part of a Hadoop distribution, a cloud-based data lake or a data preparation tool) will improve data usability, trust and shareability only in the context of that particular tool.
- Data Catalogs are just that — catalogs. The knowledge gleaned from cataloging information assets (of all kinds) can be used in many use cases, and each use case will have other technology-enabled requirements that need to be evaluated independent of the catalog itself. As such, vendors offering “catalog” capability are not all “catalog” vendor per se, some might be focused on analytics development, some on data and analytics governance. Be aware and evaluate like vendors accordingly.
- Finally, give due preference to business focused catalogs that appeal to the business teams and use embedded machine learning capabilities to rapidly simply and (in some cases) even automate the data catalog process.

Business Impact: Data catalogs will:

- Contribute to the ability to achieve insight from critical business data that is currently difficult to integrate and analyze due to the inability of organizations to inventory and curate their distributed, heterogeneous data assets.
- Support evolving nonrelational data initiatives (including data lake initiatives) by highlighting the data that is available.
- Enhance the organization’s ability to share and curate the data at its disposal across teams, functions, environments and processes.
- Coordinate and enhance data and analytics governance processes as a business-enabling capability.

Benefit Rating: High

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Sample Vendors: Alation; Attivio; Collibra; Informatica; Unifi; Waterline Data

Recommended Reading: “Data Catalogs Are the New Black in Data Management and Analytics”

"Applied Infonomics: Use a Modern Data Catalog to Measure, Manage and Monetize Information Supply Chains"

"Market Guide for Data Preparation"

"Magic Quadrant for Metadata Management Solutions"

"Magic Quadrant for Insight Engines"

Embedded Analytics

Analysis By: Kurt Schlegel

Definition: Embedded analytics is a digital workplace capability where data analysis occurs within a user's natural workflow, without the need to toggle to another application. Moreover, embedded analytics tends to be narrowly deployed around specific processes such as marketing campaign optimization, sales lead conversions, inventory demand planning and financial budgeting.

Position and Adoption Speed Justification: Some level of descriptive reporting has always been available from ERP, CRM and HCM vendors (for example, SAP, Oracle, Salesforce and Workday). However, more-flexible and comprehensive embedded analytics capabilities for diagnostic, predictive and even prescriptive analytics are becoming a necessary and differentiating component of business applications. The seamless availability of analytics as an inbuilt decision-making capability can mean that nontechnical business users may not even recognize that they are "doing analytics," particularly when this capability is deployed in support of operational decision making.

During the next five years, embedded analytics built into business applications will move from a differentiating capability to a standard feature. Differentiation will not only come from the sophistication of advanced analytics and machine learning capabilities that will be embedded, but also for how streamlined embedded analytics will become within a user's natural workflow.

We shifted time to plateau from 5-10 to 2-5 years because of the focus business application vendors will have on embedding analytics into their products.

User Advice: Improving the digital dexterity of the workforce is a competitive necessity often overlooked by HR and IT groups. In a digital workplace, however, a variety of new tools and services creates a great opportunity to improve the digital dexterity and data-driven culture of the workforce. Promoting the democratization of analytics can lead to greater employee engagement and agility, since employees need to learn new skills and contribute to better business results. The chief data officer, together with HR leaders, can better support the business by finding and deploying easy-to-use embedded analytics in circumstances that range from personal performance to critical business systems.

Don't confuse embedding analytics in business applications with purchasing packaged analytic applications. Packaged analytic applications are predefined data integrations, semantic models and analytic content that are not necessarily embedded in a workflow or business application.

Consider embedded analytics as a way to drive usage by removing barriers to adoption. Also, consider embedded analytics as way to increase business value by making analytics closer to the business process and therefore more actionable.

Embedded analytics will also be a part of strategies to help employees understand and improve their personal and team performance. Workplace metrics, measures and targets are a vital part of shaping expectations around individual employee and team behaviors. Select workplace analytics scenarios that are relevant to current business or organizational challenges, and ensure that workplace metrics encourage the desired employee behaviors that are in alignment with organizational strategy and values. When the right behaviors are encouraged — and when employees can see the benefit to themselves, the team and the organization — the overall business performance improves.

Business Impact: Embedded analytics contribute to creating an organizational culture where analytics are broadly used and trusted for decision support and personal growth within the digital workplace. Accordingly, embedded analytics will help accelerate the adoption of analytics and support data-driven decision making for specific business roles (such as finance management, sales, HR, customer service, and operations etc.) as well as for personal performance.

Benefit Rating: Moderate

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Sample Vendors: Microsoft; Oracle; Salesforce; SAP; Workday

Recommended Reading: “5 Best Practices for Choosing an Embedded Analytics Platform Provider”

“Invisible Advanced Analytics: Coming to a Business Application Near You”

Graph Analytics

Analysis By: Mark Beyer; Rita Sallam

Definition: Graph analytic techniques allow for the exploration of relationships between entities such as organizations, people or transactions. Graph analytics consist of models that determine the “connectedness” across data points to describe nodes/clusters and demarcation points. Nodes are connected explicitly or implicitly, indicating levels of influence, frequency of interaction, or probability. Graph analytics are typically portrayed via multiperspective visualization for business user consumption.

Position and Adoption Speed Justification: Graph analytics climbed slightly over the Peak of Inflated Expectations due to increased awareness in early 2019. The growing adoption of graph analytics is driven largely by the need to identify and explore insights into relationships for specific business use cases. This requires analysis across an exponentially larger amount of heterogeneous data, which is not well-suited to relational storage and analysis. These highly complex models are developed and used within machine learning with the output stored in graph databases. GraphDBs present an ideal framework for storing, manipulating and analyzing the widely varied perspectives in the graph model due to their graph-specific processing languages, capabilities and computational power. At the same time, established AI techniques (such as Bayesian networks) are increasing the power of knowledge graphs and the usefulness of graph analytics by introducing further nuance in representational power.

Graph analytics processing is a core technology underlying many other advanced technologies, such as virtual personal assistants, smart advisors and other smart machines. Various platforms also use graph analytics to identify important findings.

Analytics experts are beginning to claim specialization in graph analytics, and some traditional analytics vendors are offering capabilities that enable users to build interactive network graphs. Many providers are introducing graph engines embedded in their platforms, which means that some of the adoption curve will remain almost hidden. Importantly, the utilization of graph analytics is necessary in order to develop knowledge graphs — a highly useful output of graph analytics. Commercialization of graph analytics is still at quite an early stage, with a small number of emerging players. The method of storing and processing data within graph databases differs from traditional relational data, creating a demand for new skills related to graph-specific knowledge, which may limit growth in adoption. Examples of the new skills required include knowledge and experience with the Resource Description Framework (RDF), Property Graphs, SPARQL Protocol and RDF Query Language (SPARQL), and emerging languages such as Apache TinkerPop or the recently open-sourced Cypher.

User Advice: Data and analytics leaders should evaluate opportunities to incorporate graph analytics into their analytics portfolio and strategy. This will enable them to address the high-value use cases that are less-suited to traditional SQL-based queries and visualizations (such as computing and visualizing the shortest path, or the relationship between, and influence of, two nodes or entities of interest in a network). They should also consider using graph analytics to enhance pattern analysis. In a more recent development, metadata analysis has shown graph analysis to be specifically high value.

The user can interact directly with the graph elements to find insights, and the analytic results and output can also be stored for repeated use in a graph database.

Relational analytics is typically ideal for structured, static data in columns and rows in tables. Graph analytics, by contrast, is a new kind of lens for exploring fluid and indirect relationships between entities across multistructured data. It can deliver the kind of insight that is difficult to reach with SQL-based relational analytics.

Business Impact: Graph analytics is highly effective at both assessing risk and responding to it to analyze fraud, route optimization, clustering, outlier detection, Markov chains, discrete-event simulation and more. The engines used to expose fraud and corruption can also be used to identify similar issues within the organization and answer issues of liability in a proactive manner. They can also be used to identify peculiarly successful operating units within a larger organization to analyze if their patterns can be repeated. Once a graph process is completed, it can be visualized — using size, color, shape and direction — to represent relationship and node attributes.

A now-classic example of identifying networks of relationships is the International Consortium of Investigative Journalists (ICIJ) research, which revealed the Panama Papers.

Graph analytics can extend the potential value of the data discovery capabilities in modern business intelligence and analytics platforms. Once a graph process is completed, it can be visualized — using size, color, shape and direction — to represent relationship and node attributes. Additionally, graph analytics enable causality and dependency analyses, therefore increasing transparency in predictive models.

Business situations in which graph analytics constitute an ideal framework for analysis and presentation include:

- Route optimization
- Market basket analysis
- Fraud detection
- Social network analysis
- CRM optimization
- Location intelligence
- Supply chain monitoring
- Load balancing
- Special forms of workforce analytics, such as enterprise social graphs and digital workplace graphs
- Recency, frequency, monetary (RFM) analysis of related networks of objects, assets and conditions

There are also more-specialized applications:

- Law enforcement investigation
- Epidemiology
- Genome research

- Detection of money laundering

Benefit Rating: High

Market Penetration: 1% to 5% of target audience

Maturity: Adolescent

Sample Vendors: Cambridge Semantics; Centrifuge Systems; Databricks; Digital Reasoning; Emcien; Maana; Palantir; Symphony AyasdiAI; SynerScope

Recommended Reading: "Combine Predictive and Prescriptive Analytics to Solve Business Problems"

"Best Practices for Designing Your Data Lake"

Prescriptive Analytics

Analysis By: Carlie Idoine; Peter Krensky

Definition: "Prescriptive analytics" are a set of capabilities that specify a preferred course of action to meet a predefined objective. The most common types of prescriptive analytics are optimization methods, a combination of predictive analytics and rules, heuristics, and decision analysis methods. Prescriptive analytics differs from descriptive, diagnostic and predictive analytics in that the technology explores multiple outcomes and provides a recommended (and sometimes automated) action.

Position and Adoption Speed Justification: From a "purist" perspective, the term "prescriptive analytics" is a broad category with little hype. The broad category encompasses components with varying positions across the Hype Cycle and various levels of maturity. Such components include optimization, rules plus predictive techniques and decision intelligence.

The concepts of optimization and decision analysis have existed for decades. However, they have sustained a recent resurgence due to maturing and expanding data science initiatives, better algorithms, more cost-effective cloud-based computing power and a substantial increase in available data. In addition, the focus on the business prioritization of providing actionable, proactive insight — as opposed to the more traditional reactive reporting — has further fueled the resurgence. Many use cases are well-established, and some organizations are fairly productive with these techniques. These include optimization in supply chain and logistics, or combining predictive scores with business rules for credit and lending decisions, database marketing and churn management. New use cases continue to emerge. As adoption steadily broadens, expectations for prescriptive analytics continue to exceed reasonable expected value. Even longstanding use cases can fall victim to common data science challenges such as data quality, bias and talent shortages.

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Although it is a necessary competence, prescriptive analytics does not automatically result in better decision making. With improvement in analytics solutions, data quality, skills and broader use of predictive analytics, prescriptive analytics will continue to advance, reaching the Plateau of Productivity in two to five years.

User Advice: Data and analytics leaders should:

- Start with a business problem or decision where there are complicated trade-offs to be made, multiple considerations and multiple objectives.
- Look for packaged applications that provide specific vertical or functional solutions, and service providers with the necessary skills.
- Understand the breadth of prescriptive analytics' approaches and decision models available, and which best cater to the nature of your specific business problems and skills.
- Gain buy-in and willingness from stakeholders — ranging from senior executives to front-line workers carrying out the recommended actions — to rely on analytic recommendations.
- Ensure that your organizational structure and governance will enable the company to implement and maintain functional, as well as cross-functional, prescriptive analytics recommendations.

Business Impact: Prescriptive analytics can be applied to strategic, tactical and operational decisions to reduce risk, maximize profits, minimize costs, or more efficiently allocate scarce or competing resources. Importantly, prescriptive analytics can be deployed to improve performance because it recommends a course of action that best manages the trade-offs among conflicting constraints and goals. Significant business benefits are common and are obtained by improving the quality of decisions, reducing costs or risks, and increasing efficiency or profits.

Common use cases include customer treatments, loan approvals, claims triage, and many kinds of optimization problems such as supply chain or network optimization and scheduling. Prescriptive analytics can also be a business differentiator for planning processes, whether it be financial or production or distribution planning, allowing users to explore multiple scenarios and compare recommended courses of action.

Although prescriptive analytics has been traditionally relegated to strategic and tactical time horizons, more advanced capabilities can support real-time or near-real-time decision making. This can support automation of some operational decisions.

Benefit Rating: High

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Sample Vendors: AIMMS; Decision Lens; FICO; Frontline Systems; Gurobi Optimization; IBM; River Logic; SAS; Sparkling Logic; Veriluma

Recommended Reading: "Combine Predictive and Prescriptive Techniques to Solve Business Problems"

"Forecast Snapshot: Prescriptive Analytics Software, Worldwide, 2019"

"The 2019 Top Supply Chain Technology Trends You Can't Ignore"

"Market Guide for Supply Chain Analytics Technology, 2018"

"The Evolving Capabilities of Analytics and Business Intelligence Platforms"

Servware

Analysis By: Jorgen Heizenberg

Definition: Servware is the convergence of data and analytics services and software. These 'software-defined services' come from a single vendor (service provider) in the form of customizable assets (or blocks) which contain both business domain content and data and analytics expertise. It is protected by intellectual property (IP), and comes as a packaged product (platform or application).

Position and Adoption Speed Justification: The traditional model of delivering data and analytics is changing because services and software are converging. It is no longer the norm for data and analytics leaders to license applications from software vendors and hire service providers to implement and craft custom-built solutions. Instead, data and analytics services vendors are either adding software applications to their services, or making software out of their services (codifying them) resulting in "servware": a blend of services and software. The whole is greater than the parts. Services and software are better able to address specific business needs when combined. In fact, servware is that combination. Servware, can be viewed as a packaged intellectual property, and comes in the form of both data and analytics platforms and applications. For most service providers, servware is something that they are actively developing and offering to the market. In fact, some customers have already implemented servware without sometimes being aware of the term servware. Servware adoption is moving fast, as it is an attractive solution to all parties, vendors and customers. However customers are just learning how to best apply servware. moving fast, as it is an attractive solution to all parties, vendors and customers. However customers are just learning how to best apply servware.

User Advice: In situations where speed is a deciding factor, and the solution is considered tactical or low-risk, data and analytics leaders should prioritize servware over traditional data and analytics services. Converged services and software are creating new players in the data and analytics services market, and disrupting the practices and behavior of existing players (including consultancies and system integrators). Servware has created new opportunities for IT leaders to weave data and analytics into the operational fabric of the business, and even to monetize the organization's domain data and analytics together with the service provider.

Business Impact: Servware accelerates the speed of data and analytics innovation, and speed is essential for digital transformation. Enterprises that are transforming from being process-driven to data-driven will start to leverage information as an asset, and they will see the greatest impact from servware. By favoring prepackaged servware over custom-built solutions, they will see a reduced need for in-house skills. They will also see an improved agility that comes with faster implementations and shorter or no development cycles. Potentially, there is also a reduced total cost of ownership (TCO) for data and analytics, as servware is often based on a pay-per-use or subscription pricing model.

Data and analytics leaders should investigate the impact of services and software convergence on their data and analytics operating models, and establish business-based, cross-functional teams to increase the data and analytics performance of the business units. They should also define domain requirements, run proofs-of-concept comparisons against their current solutions with servware, and establish a "co-development" relationship with servware vendors to generate analytics IP that can be monetized together.

Benefit Rating: High

Market Penetration: 5% to 20% of target audience

Maturity: Early mainstream

Sample Vendors: Accenture; Deloitte (ConvergeHEALTH); Infosys Nia; Periscope By McKinsey; Wipro Holmes

Recommended Reading: "Take Advantage of the Disruptive Convergence of Analytic Services and Software"

"Magic Quadrant for Data and Analytics Service Providers, Worldwide"

Analytics Governance

Analysis By: Guido De Simoni

Definition: Analytics governance is the process of assigning and ensuring organizational accountability, decision rights, risks, policies and investment decisions for business analytics, calculation rules, predictive models and algorithms. It is a component of overall data and analytics governance and is enabled with a common set of capabilities.

Position and Adoption Speed Justification: Many organizations realize the need to govern not only data, but also the analytics applied to data — particularly with the increasingly decentralization of analytics use cases. Analytics governance is often actually a conscious decision to govern analytics separately from data governance. However, Gartner interactions with clients reveal that enterprise-level governance practices and policies are still in their infancy in most organizations. Analytics are an integral part of any business strategy, but come with the risk of incorrect, insufficient, illegitimate or unethical application. Business analytics are applied throughout organizations and their ecosystems: They can introduce a heterogeneous, often siloed, landscape of analytic approaches. Business units and departments are increasingly implementing their own analytics tools and applications. The questions "Could it be analyzed?" and "Should it be analyzed?" must become integral parts of an organization's governance model, for instance, to avoid severe damage to its reputation. Analytics governance needs to ensure the viability, relevance, transparency, reproducibility, legitimacy and appropriateness of the analytics applied. Data governance and analytics governance, therefore, work in tandem and need to be effectively integrated. A conversation about this convergence is underway, but convergence is still maturing in most organizations. As organizations recognize the need to break down silos and consider the ecosystem of data and analytics governance, we expect the hype about analytics governance to lessen. We therefore also expect that analytics governance will be obsolete before it reaches the Plateau of Productivity.

User Advice: Any analytic, predictive or decision-making process is based on data models, which should be developed in accordance with data governance policies for data integrity, fidelity, quality, security, privacy and retention. Furthermore, the information assets used for analytics constitute a significant portion of the overall expense of applying business analytics.

This leads to the strategic need for a consistent application of analytics governance across the organization.

Specific recommendations:

- Extend your data governance by the inclusion of analytics governance. Don't attempt to institute analytics governance as a stand-alone initiative.
- Develop trust models for both the input data used for analysis and the resulting analytics outcomes.
- Ensure the transparency and propriety of analytics. Analytics are required in many regulated industries, but, beyond this, users might distrust "black box" analytics.
- Implement a change management approach to help your organization become fact-driven, ensure traceability and reproducibility of analysis, and, most importantly, help your organization become fact-driven.
- Don't assume your analytics, business intelligence, data science or artificial intelligence solutions support your requirements for analytics governance — most do not. At best, such solutions might respect one policy, such as user access. You will need to take it upon yourself to define requirements and evaluate solutions — and most likely add solutions designed to meet those requirements.

Chief data officers and other data and analytics leaders should ensure that analytics governance and data governance are integrated, and do not become isolated practices in different parts of the organization.

Business Impact: Analytics governance should be established in accordance with corporate and data governance policies with respect to:

- Balancing and prioritizing investment decisions for business analytics in accordance with business strategy and goals.
- Defining processes and policies on the delegation of authority and accountability for analytics decision rights.
- Ensuring legitimate and ethical use of analytic algorithms, in line with corporate values.

Failures of analytics governance can be operationally costly and high-risk. Consequences may include an inability to implement analytics due to users' resistance ("That's how we do business here!"), dissatisfaction and misinterpretation of insights. Investments in solutions to help with the task of setting and enforcing analytics governance policy may lead to additional investments beyond those you have for data governance. Over time, though, we expect capabilities to converge, so your investments will, in time, also converge.

Benefit Rating: High

Market Penetration: 1% to 5% of target audience

Maturity: Adolescent

Sample Vendors: Collibra; Waterline Data

Recommended Reading: "Use Adaptive Governance for Data and Analytics to Drive Digital Business Success"

"Use Enterprise Metadata Management to Extend Information Governance to Analytics"

Event Stream Processing

Analysis By: W. Roy Schulte; Nick Heudecker; Pieter den Hamer

Definition: An event stream is a sequence of event objects arranged in some order, typically by time. Event stream processing (ESP) is computing that is performed on event objects for the purpose of stream data integration or stream analytics (also called complex-event processing [CEP]). Stream analytics can be executed either as new data arrives (using event-driven ESP platform software); shortly after it arrives (using real-time, on-demand queries); or long after it has been stored (using on-demand queries on historical data).

Position and Adoption Speed Justification: Three factors are driving the expansion of ESP:

- The growth of the Internet of Things (IoT) and digital interactions is making event streams ubiquitous.
- Business is demanding continuous intelligence for better situation awareness and faster, more personalized decisions.
- Vendors are bringing out new products, many of them open source or partly open source, giving the impression of lower acquisition costs.

Companies have access to more streaming data from internal sources (such as sensors, meters, control systems, corporate websites and transactional applications); and from external sources (such as social computing platforms, news and weather feeds, other data brokers, government agencies and business partners). ESP technology is maturing rapidly. It will eventually be adopted by multiple departments within every large company. ESP will reach the Plateau of Productivity within five years, largely by being embedded in SaaS solutions and off-the-shelf packaged applications.

User Advice: Data and analytics leaders should:

- Use ESP when traditional DBMS architectures cannot execute fast enough to provide real-time information from high-volume event streams.
- Acquire ESP functionality by using a SaaS offering or an off-the-shelf application that has embedded CEP logic (but only if a product that addresses your specific business requirements is available).
- Build your own application on an ESP platform if an appropriate off-the-shelf application or SaaS offering is not available.
- Build your own application on an ESP platform if your company has multiple applications that need some of the same overlapping data or CEP logic, to avoid redundant or stove-piped ESP solutions.
- Use free, community-supported, open-source ESP platforms if your developers are familiar with open-source software and languages such as Java, Scala or Python, and license fees are the primary consideration. Use vendor-supported closed-source platforms or products that mix an open-source core with value-added closed-source extensions for mainstream applications that require enterprise-level support and more complete sets of features.
- Use on-premises ESP in preference to cloud event processing services for ultra-low-latency applications such as high-frequency financial trading, and for applications where most of the data originates on-premises.

- Use ESP technology that is optimized for stream data integration to ingest, filter, enrich, transform and store event streams in a file or database for later use.

Business Impact: Stream analytics provided by ESP platforms:

- Can support situation awareness through dashboards and alerts by analyzing multiple kinds of events in real-time.
- Enable smarter anomaly detection and faster responses to threats and opportunities.
- Can help shield business people from data overload by eliminating irrelevant information and presenting only alerts and distilled versions of the most important information.

ESP is one of the key enablers of continuous intelligence and other aspects of digital business. It has transformed financial markets and become essential to smart electrical grids, location-based marketing, supply chain, fleet management and other transportation operations. Much of the growth in ESP usage during the next 10 years will come from three areas where it is already somewhat established: IoT, customer experience management and fraud detection applications. More than 40 ESP products or PaaS services are available on the market.

Benefit Rating: Transformational

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Sample Vendors: EsperTech; EVAM; IBM; Microsoft; Oracle; SAP; SAS; Software AG; The Apache Software Foundation; TIBCO Software

Recommended Reading: “Market Guide for Event Stream Processing”

“Adopt Stream Data Integration to Meet Your Real-Time Data Integration and Analytics Requirements”

“The Five Levels of Stream Analytics — How Mature Are You?”

“Technology Insight for Event Stream Processing”

“Innovation Insight for Continuous Intelligence”

Sliding Into the Trough

Data Lakes

Analysis By: Nick Heudecker

Definition: A data lake is a concept consisting of a collection of storage instances of various data assets. These assets are stored in a near-exact, or even exact, copy of the source format and are in addition to the originating data stores

Position and Adoption Speed Justification: As a concept, data lakes have entered the Trough of Disillusionment. There is significant confusion about what a data lake is, how it compares to concepts like data warehouses and data hubs, and how it supports different user groups and service-level agreements. Based on conversations with Gartner clients, many data lake implementations are being designed to serve data scientists, business analysts and casual users. Because many implementation technologies aren't optimized for these kinds of diverse workloads, these companies experience challenges with data governance, data quality, and overall performance.

As more organizations embrace the data lake concept with an immature understanding of where a data lake fits into their data estates, Gartner expects to see more failures than successes over the next 5 years. However, some organizations are adopting the "data lake" term for their data warehouses. While this "data lake washing" doesn't give organizations the experimental environment that a real data lake provides, they'll likely have more success meeting the broader analytical needs in the organization.

User Advice:

- The fundamental assumption behind the data lake concept is that everyone accessing a data lake is moderately to highly skilled at data manipulation and analysis. Before implementing a data lake, ensure you have either the necessary skills, such as data science or engineering, or a plan to develop them.
- Recognize that results will likely be difficult to reproduce between analysts. By definition, data stored in data lakes lacks semantic consistency and data governance of any kind. Dispensing with these makes data analysis highly individualized (a consumerization of IT goal) at the expense of any easy comparison or contrast of analytic findings (also indicative of consumerization of IT).
- There are certain SLA expectations that can be served by data lakes. However, the majority of end-user SLAs for analytics rely on repeatability, semantic consistency and optimized delivery. Once data lake efforts confront these SLAs, it is time to explore alternative information management architectures, such as the logical data warehouse, to rationalize how information is stored with how it is used.
- Evaluate a variety of implementation options. Hadoop is typically seen as the technology choice for data lakes on-premises, but this is changing as organizations shift to the cloud. Cloud-based object stores are becoming the dominant data lake choice, but nonrelational DBMSs, in-memory data grids (IMDGs) and even relational DBMS are possible implementation options.

- Many organizations think of a data lake to share data within the organization, roughly equivalent to data as a service. This frequently results in multiple copies and lineages of data — exactly what many data lake advocates said wouldn't happen. Alternative architectures, like data hubs, are often better fits for this type of use case (see "Use a Data Hub Strategy to Meet Your Data and Analytics Governance and Sharing Requirements").

Business Impact: The data lake concept has the potential to have a high impact on organizations, but its effect is only moderate at present. To get full value from a data lake, its users must possess all the skills of a system analyst, data analyst *and* programmer. They should also have significant mathematical and business process engineering skills — otherwise it will still have a significant impact, but a highly undesirable one.

Depending on the method of implementation, a data lake can be a low-cost option for massive data storage and processing. Processed results can be moved to an optimized data storage and access platform, based on business requirements and tool availability. However, the potentially high impact of this will be diluted by vendors seeking to use the term "data lake" merely as a means of gaining entry to the highly mature analytics and data management markets. This presents the potential for some very real lost opportunities and large sunk costs when a balanced warehouse/services/lake architectural approach would be the better solution.

Benefit Rating: Moderate

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Sample Vendors: Amazon Web Services; Cambridge Semantics; Cazena; Informatica; Microsoft; Zaloni

Recommended Reading: "Use Design Patterns to Increase the Value of Your Data Lake"

"Solve Your Data Challenges With the Data Management Infrastructure Model"

"Efficiently Evolving Data From the Data Lake to the Data Warehouse"

"Derive Value From Data Lakes Using Analytics Design Patterns"

"Use a Data Hub Strategy to Meet Your Data and Analytics Governance and Sharing Requirements"

"Best Practices for Designing Your Data Lake"

"Metadata Is the Fish Finder in Data Lakes"

Analytics and BI Platform as a Service

Analysis By: Austin Kronz; Joao Tapadinhas

Definition: Analytics and BI platform as a service — cloud ABI — delivers analytics capabilities and tools as a service. Cloud ABI platforms often comprise database, integration capabilities and business analytics tools — or solutions that include only business analytics tools. Most leverage autonomous cloud-based data repositories but some can query on-premises data repositories directly. As cloud deployments continue, the ability for platforms to connect to both cloud-based data sources and on-premises sources in a hybrid model is increasingly important.

Position and Adoption Speed Justification: There is a growing interest in and adoption of cloud ABI. Having past a tipping point in 2017, adoption of cloud analytics and BI continued through 2018. Most net new deployments are originating in the cloud, and the majority of respondents from a recent Gartner survey say they have plans to adopt some form of cloud within the next year. Organizations' adoption of the cloud is closely tied to data gravity — the concept that as the amount of data grows and levels of customization, integration and varying access needs increase, the greater propensity that data has to "pull" data services, applications and even other data/metadata to where that data resides. It follows that smaller organizations with data originating in the cloud have higher adoption rates than larger organizations with predominantly on-premises legacy solutions. Analytics solutions, such as Microsoft Power BI which relies on Microsoft Azure for dashboard publishing, and stronger cloud ABI solution in general, are changing this pattern and bringing organizations of all sizes to the cloud.

There is a growing range of solutions available, with most of the vendors in the market providing solutions as alternatives to on-premises products. Moreover, startups continue to join the BI market with cloud-only solutions and seem happy in many cases to skip the on-premises market.

The range of capabilities is growing too. Reports and dashboards were already common offerings, but customers can now also subscribe to data discovery, self-service data preparation, augmented data discovery, predictive modeling, other advanced capabilities such as machine learning or streaming analytics, and even data/context broker services from several vendors. Cloud-based data warehousing, based on dbPaaS, is also helping support and expand this market.

In summary, hype around cloud ABI continues to be high, but is now facing growth pains as organizations face deployment challenges. Cloud ABI is going through the Trough of Disillusionment as it confronts the data integration aspect between on-premises solutions and the cloud.

User Advice: Cloud ABI is moving toward becoming a valid option in many scenarios in the business analytics space, but there are still some important gaps and potential problems. Security might look like the No. 1 concern for organizations when moving to the cloud, but that may not always be the case. Organizations need to plan how they will integrate their growing cloud ABI deployments with additional data sources, provide access to third-party analytic tools, and embed analytics in business processes — all of this in combinations of on-premises and cloud.

As more vendors and solutions move into this space and the analytics ecosystems of some vendors grow — such as Amazon, IBM, Microsoft, Oracle, Salesforce and SAP — the integration across various platforms should become easier to solve.

Organizations wanting to gain competitive advantage through analytics and BI should start to include innovative cloud ABI solutions in their portfolio, renovating components or complementing their on-premises platform. They should be mindful, though, that the market doesn't yet have solutions for all the issues that have been solved on-premises, or provides the same level of interoperability. Also, they should be aware that some capabilities are still better delivered by on-premises solutions. Hybrid solutions with on-premises and cloud components will be the solutions for best-of-breed portfolios.

From a cost perspective, although not requiring upfront investment like on-premises solutions do, cloud ABI solutions will likely have a more expensive global licensing cost, when considering periods of four or more years, compared to the on-premises solutions.

Business Impact: Cloud ABI products offload server infrastructure and the administration/support burden, while allowing IT and business teams more time to focus on analyzing the data that drives business performance. Clients that have embarked on these initiatives cite three approaches that affect their organizations.

- **Augmentation —** Using cloud ABI to augment an on-premises business analytics system — such as providing an analytic sandbox, leading to a faster time to value and more targeted analytics deployment for specific business areas.
- **Replacement —** Using cloud ABI to replace key components of the business analytics infrastructure, usually starting with a line of business or a particular type of content. For some, this "replacement" model is used to prove the concept and value of cloud ABI.
- **Process enablement —** Using cloud ABI to enable cross-enterprise collaboration and planning, opening up data analysis for sharing between constituents in an extended value chain.

Compared with on-premises deployments, cloud ABI should give users faster time to value, lower initial costs and less need to maintain expensive skills to support a hardware- and software-rich analytics platform.

Benefit Rating: Moderate

Market Penetration: More than 50% of target audience

Maturity: Early mainstream

Sample Vendors: Domo; Infor (Birst); Microsoft; MicroStrategy; Oracle; Qlik; Salesforce; SAP; Tableau Software; TIBCO Software

Recommended Reading: "Magic Quadrant for Analytics and Business Intelligence Platforms"

“Critical Capabilities for Analytics and Business Intelligence Platforms”

“Survey Analysis: Analytics and BI Platform Software License Fees Continue to Drop”

“Platform as a Service: Definition, Taxonomy and Vendor Landscape, 2019”

Indoor Location Intelligence

Analysis By: Annette Zimmermann; Tim Zimmerman

Definition: Indoor location intelligence refers to services and solutions that generate, process and analyze data in an indoor environment to provide insight on the location (and movement) of objects and people from a historic, real-time or predictive perspective. The underlying technologies are wide-ranging and include Wi-Fi, BLE, infrared, ultrasound, RFID and UWB.

Position and Adoption Speed Justification: We positioned this profile post-trough. Gartner registers hundreds of location intelligence projects each year, of which some are still at POC stage, yet we are seeing also an increasing amount of full deployments at scale that deliver real business value, especially in healthcare, retail and manufacturing. The two broad use cases for location intelligence are people monitoring and asset tracking, and these can be divided into hundreds of sub-use cases.

The main issues that organizations need to deal with are technology choices and data privacy. Some technologies provide centimeter accuracy versus 4 to 5 meters. The high precision technologies tend to be more expensive, hence there is a trade-off, and organizations need to precisely define their use cases to determine what accuracy level they need.

Location data is sensitive data and hence needs to be treated as such, especially in an external client-facing situation.

User Advice: Enterprise application leaders who are looking to deploy indoor location intelligence solutions should:

- Define three to five use cases that you are looking to address and in as much detail as possible. This fine-tuned assessment of use cases will determine which technology and vendor to choose.
- Understand the direct trade-off between location accuracy and cost and deploy the technology that supports the use case. Overdelivery on accuracy will significantly increase costs, while underdelivering on accuracy will bring no value and the project may fail.
- Determine which type of customer data you will collect, store and process, and for which purpose. Set up different scenarios that categorize the data types. These categories should be location data of objects and location data of people, and then further refined by anonymized versus identifying data. This will give guidance on which data privacy regime to follow.

- Provide opt-in mechanisms for consumer-facing apps by letting users decide which personal data they want to share and ultimately how they want to engage with a brand.
- Be transparent toward staff on which and when location data is processed/stored by emphasizing the safety aspect of such a solution and the fact that their personal location data is not being tracked off-premises.

Business Impact: Gartner sees strongest growth for indoor location intelligence solutions in healthcare, retail, and manufacturing, followed by hospitality, public transport/airports and the public sector.

Business benefits/impacts are:

- Healthcare
  - Monitor mobile assets (such as infusion pumps) in real time to reduce time spent on searching and to reduce stock
  - Track patients to optimize the flow
  - Receive an alert when valuable assets are being removed
  - Monitor compliance behavior, such as hand sanitation
  - Provide wayfinding and appointment management to patients to reduce no-show rates and improve customer experience
- Retail
  - Manage staff based on monitoring customer traffic
  - Understand footfall and shopping behavior
  - Provide turn-by-turn navigation in larger shopping venues
  - Customer engagement and CX
- Manufacturing
  - Track parts/pallets to save time and reduce costs
  - Collision avoidance/accident prevention
  - Worker safety — use geofencing to warn employees of dangerous zones/equipment
  - Monitor idle tools

- Access control

- Public sector
  - Locating assets and people in an emergency
  - Improve evacuation process
  - Access control

Benefit Rating: High

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Sample Vendors: AiRISTA Flow; Aruba Networks; Cisco; Cloud4Wi; Esri; Purple; Quuppa; STANLEY Healthcare; Zebra

Recommended Reading: "Magic Quadrant for Indoor Location Services, Global"

"Market Guide for Indoor Location Application Platforms"

Climbing the Slope

In-DBMS Analytics

Analysis By: Adam Ronthal

Definition: In-DBMS analytics (also known as in-database analytics or in-database processing) constitutes the integration of analytics into the database management system (DBMS) platform. This approach pushes data-intensive processing — such as data preparation, online analytical processing, predictive modelling, operations and model scoring — down into the DBMS platform, close to the data, in order to reduce data movement and support rapid analysis.

Position and Adoption Speed Justification: In-DBMS analytics continues to gain traction with data scientists, its natural constituency, but adoption remains sporadic due to a general preference for familiar tools like R, Python, and notebooks (Project Jupyter, Apache Zeppelin). However, with an increasing number of DBMS vendors now integrating familiar tools and interfaces for use with in-DBMS analytics, this is starting to shift. In-DBMS analytics provide an environment for moving analytic models to production with model generation and execution in the same environment. A common development pattern allows for models to be developed using familiar data science tools, and deployed in production using native SQL interfaces to in-DBMS algorithm libraries.

In-DBMS analytics is becoming increasingly relevant — especially to enterprisewide business analytics — due to the persistent growth in multistructured data from digitalization, the need to reduce time-to-insight through rapid processing of large volumes of data using machine learning techniques, and the position of strength that the DBMS vendors have in this area as the foundation for data persistence. These capabilities make relational DBMSs a viable and attractive choice for exploratory data science work.

In-DBMS analytics offerings have been available from specialized vendors for years, and most of today's mainstream DBMS vendors — both cloud and traditional — are offering some kind of in-DBMS analytic capabilities. Tighter integration between familiar data science and machine learning tools like R and DBMS offerings (from the same or different vendors) are also driving adoption of this approach. DBMSs already have the core foundation to enable advanced analytics — including parallelization, in-memory capabilities, multistructured read/write capabilities, security and platform independence. These capabilities align well with the increasing demand for distributed, flexible and scalable analytics. The existing functionality of modern DBMS platforms makes them the strongest contender for servicing this demand. Additionally, the next wave of capabilities is starting to emerge in this space as some vendors take an approach that tightly integrates the underlying relational structures of the DBMS with machine learning and tensor algebra.

In-DBMS analytics have met with early successes in life sciences, retail analytics, risk analytics, natural resource exploration, oil and gas, and other data-intensive use cases.

User Advice: Data and analytics leaders should consider in-DBMS analytics as a viable option for making large-scale business analytics available to a wider audience by embedding the capabilities in familiar and pervasive platforms that can deliver rapid insights on both historical and incoming data. By avoiding the need to move data out of the DBMS to build analytic models, in-DBMS analytics allows for more flexible experimentation and efficient development of models and applied use cases that can serve as a foundation for broader, robust and reliable delivery.

A number of mature in-DBMS analytics offerings are available in the market. Enterprises should scrutinize these offerings for suitability of capabilities in supporting their use cases.

Among the DBMS vendors are:

- Amazon (Redshift)
- IBM (Db2)
- Microsoft (SQL Server Machine Learning and R Services)
- MemSQL
- Micro Focus (Vertica)
- Oracle (Advanced Analytics)
- Pivotal Greenplum (Apache MADlib)

- Teradata (Teradata Vantage)
- SAP HANA Predictive Analysis Library
- relationalAI

Among the advanced analytics platform vendors that enable push down processing to multiple DBMS platforms are:

- SAS
- IBM (SPSS Software)
- MicroStrategy
- RapidMiner

Third-party vendors like Alteryx and Fuzzy Logix have also developed libraries of in-DBMS offerings and tools supporting multiple DBMS platforms.

Business Impact: In-DBMS analytics benefits enterprisewide business analytics in the following ways:

- Enables skilled users, such as application developers, to develop and consume analytics (perform forecasting, for example) directly from the DBMS, eliminating the need to move data to a dedicated analytics environment.
- Improves accuracy of analytic models by allowing them to use all the data in the DBMS, rather than a subset of data typical of approaches that require data to be moved to a dedicated analytics environment.
- Realizes cost savings by capitalizing on existing investments in DBMS and analytics platforms through reuse while also representing the path of least resistance for adding functionality to the data management architecture and infrastructure.
- Enables delivery of rapid insights by leveraging DBMS optimization features such as in-memory architecture.

Provides easier and faster deployment by allowing derived models to be invoked in production instances of the DBMS.

Benefit Rating: High

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Sample Vendors: Alteryx; Fuzzy Logix; IBM; Microsoft; Oracle; Pivotal; relationalAI; RapidMiner; SAP; Teradata

Recommended Reading: "Why In-DBMS Analytics Deserves a Fresh Look"

"Magic Quadrant for Data Science and Machine Learning Platforms"

"Magic Quadrant for Data Management Solutions for Analytics"

Predictive Analytics

Analysis By: Peter Krensky; Alexander Linden; Carlie Idoine

Definition: Predictive analytics is a form of advanced analytics that examines data or content to answer the question, "What will happen?" or more precisely, "What is likely to happen?" It is characterized by techniques such as regression analysis, multivariate statistics, pattern matching, predictive modeling and forecasting.

Position and Adoption Speed Justification: The excitement surrounding predictive analytics continues to drive more interest and adoption at all maturity levels. Levels of project underperformance and ROI failure are low and this technology has quickly crossed Trough of Disillusionment as the rate of evolution and underlying value of predictive analytics drives the technology rapidly toward the Plateau of Productivity in the near future.

From those just getting started with predictive analytics to enterprises with mature data science labs, organizations are evangelizing the value and potential impact of predictive models. Interest is also driven by improved availability of data, lower-cost compute processing (especially in the cloud) and proven real-world use cases. Predictive models are no longer just produced by data science platforms; predictive analytics is embedded in more business applications than ever before. Client searches on gartner.com for "predictive analytics" continue to trend steadily upward.

User Advice: Predictive analytics can be quite easy to use if delivered via a packaged application or an AI cloud service. However, packaged applications pretrained models do not exist for every analytics use case. Packaged applications and AI cloud services may also often not provide enough agility, customization or competitive differentiation. In these situations, organizations are advised to build solutions either through an external service provider, or with typically highly skilled in-house staff using a combination of open-source technologies and a data science platform. Many organizations increasingly use a combination of these tactics (buy, build, outsource) and some vendors have hybrid offerings. Finally, to secure the success of predictive analytics projects, it is important to focus on an operationalization methodology to deploy these predictive assets.

Business Impact: By understanding likely future outcomes, organizations are able to make better decisions and anticipate threats and opportunities, being proactive rather than reactive (for example, predictive maintenance of equipment, demand prediction, fraud detection, and dynamic pricing). Interest and investment continues to grow in both new use cases, and more traditional applications of predictive analytics (for example, churn management, cross-selling, propensity to purchase, database marketing, and sales and financial forecasting).

Benefit Rating: High

Market Penetration: 20% to 50% of target audience

Maturity: Early mainstream

Sample Vendors: Alteryx; DataRobot; H2O.ai; IBM; KNIME; MathWorks; Microsoft; RapidMiner; SAS; TIBCO Software

Recommended Reading: "Combine Predictive and Prescriptive Techniques to Solve Business Problems"

"Data Science and Machine Learning Solutions: Buy, Build or Outsource?"

"Magic Quadrant for Data Science and Machine Learning Platforms"

"Critical Capabilities for Data Science and Machine Learning Platforms"

Outdoor Location Intelligence

Analysis By: Bill Finnerty; Jim Hare

Definition: Outdoor location intelligence (OLI) is the process of deriving meaningful insight from geospatial data relationships — people, places or things — to solve particular challenges such as demographic analysis, store placement, asset tracking, environmental analysis and traffic planning.

OLI consists of a combination of GIS software, web mapping solutions, position technologies such as GPS and location-based data.

Position and Adoption Speed Justification: Location is one of the most significant means of contextualizing user and sensor data. Outdoor location intelligence, founded in geospatial and location intelligence, presents an ever-growing set of use cases in marketing, smart cities, Industrie 4.0, transportation and other industries.

Maturing OLI tools increasingly support business line functionality. In addition to GIS vendors and those embedding OLI in applications, business intelligence (BI) and other data visualization solution providers regularly provide OLI capabilities. These solutions frequently enable "citizen analysts" to leverage OLI data to perform spatial analysis to improve operations; discover new business and service delivery opportunities; and communicate with stakeholders, customers and constituents.

The cost of data acquisition and privacy and data laws are major barriers to OLI adoption. The use of location data of people for surveillance increasingly alarms citizens and employees. Data, although available in increasingly shorter intervals, can price projects without a clear return on investment (ROI) beyond organizations' reach.

User Advice: IT leaders need to provide the platform that will empower business units to leverage outdoor location intelligence to improve analysis, service delivery and business processes. Develop and share relative use cases and examples that will inspire business stakeholders to leverage outdoor location intelligence in new ways, while also insisting that they clearly define the business value or ROI.

Establish a spatial data management strategy or include spatial data in an existing data management strategy to improve the quality and use of spatial data. Create a framework for determining the best means for acquiring data: using open data, developing new datasets, utilizing data as a service or purchasing new data. Develop a data management approach that exposes data catalogues to maximize data reuse and promote data sharing.

As tools and applications place outdoor location intelligence in the hands of more end users, organizations need to develop the skills of citizen analysts to improve understanding of spatial analysis and relative capabilities. Establish a spatial data and analysis training program, or extend current efforts, to include a broader set of users. Include data governance, data standards, spatial analysis and visualization techniques.

Business Impact: Outdoor location intelligence can reveal new opportunities, based on location and spatial relationship, that were previously not identified for business and government. These opportunities manifest as improved operations, new marketing and engagement chances and enhanced decision making.

Industry-specific use cases include:

- Combining business data with location data to visualize customer and revenue data on geographic maps to identify sales and marketing opportunities
- Using outdoor location intelligence for predictive policing and public safety to better position resources to improve response time
- Using location data to inform customer journeys that track and analyze how customers and prospects use available channels to interact with an organization over time
- Using online maps in economic development and community planning applications in the public sector to aid entrepreneurs in site selection
- Leveraging geofencing, location data and temporal data to market discounts on take-out food by restaurants

- Using fraud pattern prevention/detection in underwriting clearance and claims network management in insurance

Benefit Rating: High

Market Penetration: 20% to 50% of target audience

Maturity: Early mainstream

Sample Vendors: Alteryx; CARTO; Esri; HERE Technologies; Mapbox; Microsoft; Pitney Bowes (MapInfo); Planet; Qlik; TIBCO Software (Spotfire)

Social Analytics

Analysis By: Melissa Davis

Definition: Social analytics applications assist organizations in the process of collecting, measuring, analyzing and interpreting the results of interactions and associations among people, topics, ideas and other content types on social media.

Position and Adoption Speed Justification: We see the following business, technology and societal trends that increase the business impact of the insights and advance the technology while at the same time change the dynamics of the market:

Adoption of social analytics across the enterprise. Social analytics has yet to hit the Plateau of Productivity due to its reduced value proposition within enterprises. This is due to reporting being one-off which makes it look reactive in nature. The reactive perception inhibits business leaders from leveraging the information toward impactful business change. A key challenge is social analytics being managed by social media team rather than a broader analytics team, CRM team or HR team, for example. Social analytics has become minimized because people view it as a one-off report rather than information critical to impacting business change.

Increased adoption of advanced analytics including ML/AI: Many vendors have advanced their offerings from basic rules based key word searches to apply natural language processing (NLP), clustering and machine learning technologies to enhance sentiment analysis, analyze patterns across the buying and owning journey and predict outcomes.

Growing diversity of data sources analyzed beyond text, including image and video, although video very nascent. Social media analytics started with and continues to be based on text analytics. The broader and more diverse the data analyzed, the more potential value in the insights.

Concerns about violent, politically charged, extremely misleading or other kinds of content that attract the scrutiny of citizens, law enforcement and governments. Due to the recent focus on user data misuse, Facebook (which also owns Instagram) is further limiting how much data vendors can collect from its API. 2018 was the worst year ever for Facebook data breaches and 2019 has brought more damning publicity, with controversies about allowing violent events to be viewed in real time and subsequently spread via the platform. There are also recent reports on a data breach involving a half a billion Facebook files, the largest yet to reach the public domain (citation). In response, various nations and transnational entities have drafted legislation attempting to make the corporation legally responsible for user content on their platform. Although these early attempts are being described as 'vague' and 'unenforceable', they will doubtless continue and become more precise and effective. In a way, this is an opportunity for social analytics vendors, who may be able to help identify unacceptable content that Facebook will need to block or remove. It will take time to see how other platforms have emerged and how this impacts social analytics tools.

Regardless, we expect to see continuous improvement in making social analytics a critical part of decision making and productivity within the next two to five years. However, we believe that market consolidation is inevitable.

User Advice: Take advantage of social analytics in order to monitor, discover and predict behavior. They must also know what questions to ask and plan what to do with the information they uncover in order to derive value from social analytics.

Create the business case around qualified leads, revenue generated, cost savings or even risk reduction, for example how can social media analytics anticipate or curtail brand or reputational risk?

Organize cross functional teams across CRM, HR, Product to promote social analytics as critical to impacting business change across the organization and not just siloed, one off reports from a social media team.

Work with their main analytics vendors to understand if and how their offerings can be integrated with social data. What acquisitions will they make, if any? Will you be able to integrate your VoC or CRM applications to make the data even more valuable?

Plan for image and audio analysis in addition to text analytics and evaluate vendors accordingly. Think about AI enhancements to your social media analytics program or how social data can be used in AI-driven processed and decisions.

Business Impact: Social analytics is useful for organizations that want to make real-time decisions and predict future trends based on social media's collective intelligence. For example, a biopharmaceuticals researcher could examine medical research databases for the most influential researchers by first filtering for the search terms and then generating a social network of researchers publishing in that field. Similarly, social analytics could be used by marketers wanting to measure the impact of advertising campaigns or to uncover a new target market for their products. They could look for behaviors among current or prospective customers that could help to spot:

- Trends, such as deterioration in customer satisfaction or loyalty
- Behaviors, such as demonstrated interest in specific topics or ideas
- Early warning signals, such as drug side effects to disease outbreaks, sources of customer satisfaction and process breakdowns

Benefit Rating: High

Market Penetration: 20% to 50% of target audience

Maturity: Early mainstream

Sample Vendors: Brandwatch; Clarabridge; Khoros; NetBase; Oracle; Salesforce (Social Studio); Sprout Social; Synthesio; Talkwalker; Zignal Labs

Recommended Reading: "Market Guide for Social Analytics Applications"

"RFP Toolkit: Social Analytics Applications for CRM"

"How to Apply Advanced Analytics Capabilities to Social Data"

"Top Use Cases and Benefits of Social for CRM in 2018"

Logical Data Warehouse

Analysis By: Mark Beyer; Adam Ronthal

Definition: The logical data warehouse (LDW) is a best-practice analytics data management architecture and design that combines the strengths of traditional repository warehouses with alternative data management and access strategies. It has replaced the prior generation of Kimball/Inmon hybrid warehouses in leading organizations and is effective for cloud deployments.

Position and Adoption Speed Justification: Continuing in 2019, the market adoption of the LDW has increased to more than 18% of all data warehouse deployments. Different implementers have applied different names to this approach, including "modern data warehouse" and "smart data warehouse." All are essentially the same architecture and design. Recent indications show that dynamic optimization, and even dynamic "switching" between processing and data storage, have begun. The capability to utilize integrated or independent data access tiers permits distributed deployments even on differing platforms; combining mixed data infrastructures has, in effect, become the "new" data warehouse.

Many organizations are seeking approaches to combine various data marts and/or existing enterprise data warehouses (EDWs) with the newest data lake deployments on both premises and cloud. The location of data in the joined repositories is more fluid than in the past. Organizations use the LDW approach to combine traditional data warehouse infrastructure that has moved to a data warehouse in the cloud, or even data warehouse as a service, with other forms of analytic data processing. Importantly, the LDW is an architectural design — it is not a purchased commodity.

Wide adoption encourages marketing to misrepresent known defective solutions combined with mistaken techniques. For example, recognizing that a lake and the warehouse are two different designs, but the platform for deployment can be the same or separate. The LDW is not a “data warehouse in the data lake.”

Alternatively, existing data warehousing leaders have reworked their solutions to extend the administration and control functions, and subsume other platforms (for example, Apache Hadoop under IBM, Oracle or Teradata). Vendors find it difficult to reestablish their credibility even though their solutions are proven. Similarly, newer providers focusing on the semantic tier (such as Denodo) are finding success. We see many options for deploying and designing the LDW. Data virtualization remains a popular choice for creating the requisite semantic tier, as well as newer technologies that leverage Apache Arrow such as Dremio. A cloud-based DBMS can be a semantic and processing tier such as Snowflake, which may also contain data files.

User Advice:

- Data and analytics leaders, such as business intelligence (BI) and data warehouse architects, should evaluate pilot projects and test cases for combining “big data” solutions (archaic) with traditional analytic data stores. They should then determine the most appropriate method for providing combined data, based on existing skills, platform preferences, use-case demands, budgetary constraints and user types. The LDW does not alter the underlying performance and design characteristics of existing data stores that it accesses.
- Leaders should pursue accurate cost evaluations for deploying, maintaining and accessing information in data lakes, and determine if processes can be migrated to repetitive transform-and-load jobs in the primary warehouse. Existing extraction, transformation and loading (ETL) jobs may also be candidates for migration off the data warehouse platform and back to data lake technology. In use cases where compromise models are not possible for portraying data, consider a semantic tier or a distributed processing solution.
- Develop a series of standards that determine when analytic data will be stored in repositories, made available via a semantic and/or virtual tier, or kept in a processing language environment to leverage distributed processing on clusters. To achieve this, use data stability and pervasive analytic models as a guide. Then implement according to these standards and enforce their use.

Business Impact: The LDW allows for faster exploration of new data assets by qualified and skilled users. At the same time, it provides a framework that allows the work of highly skilled analysts and data scientists to be “promoted” into production runs. Those production runs usually result in metrics, indicators or lists that are more easily rendered in production dashboards or reporting systems for less-skilled analyst users. The LDW is both an evolution and an augmentation of existing data warehouse architecture practices. It is also an approach for starting a data lake initiative and building “backward” to combine them with traditional data warehouse solutions as needed. It reflects the fact that not all analytical, querying and reporting needs can be supported by a traditional, centralized, repository-style data warehouse, nor, conversely, by data lake implementations. It implies a much broader and more inclusive data management solution for analytics.

The LDW provides a more reliable way to respond to new analytical or reporting demands with short time-to-delivery requirements, and with a large number of datasets made available via query tools and applications. In this way, it accelerates data warehouse modifications and provides a rapid deployment capability for new sources with gradually maturing use cases. The LDW can even use a data lake as a source, or one of the underlying data stores.

Benefit Rating: High

Market Penetration: 5% to 20% of target audience

Maturity: Early mainstream

Sample Vendors: Amazon Web Services; Cloudera; Databricks; Denodo; IBM; Microsoft; Oracle; Pivotal; Snowflake; Teradata

Recommended Reading: “The Practical Logical Data Warehouse: A Strategic Plan for a Modern Data Management Solution for Analytics”

“Organizing Your Teams for Modern Data and Analytics Deployment”

“Critical Capabilities for Data Management Solutions for Analytics”

“Efficiently Evolving Data From the Data Lake to the Data Warehouse”

“Adopt the Logical Data Warehouse Architecture to Meet Your Modern Analytical Needs”

Text Analytics

Analysis By: Stephen Emmott; Alexander Linden; Marko Sillanpaa

Definition: Text analytics is the process of deriving business insight or automation from text. This process can include determining and classifying the subjects of texts, summarizing texts, extracting key entities from texts, and identifying the tone or sentiment of texts.

Position and Adoption Speed Justification: Text analytics addresses a diverse range of uses from general capabilities, to extracting data from textual content, to industry-specific and line-of-business use cases. Typically, vendors supporting text analytics do so in the form of applications that, although built on a general capability, are tailored to specific categories of use case (for example, voice of the customer in the context of customer relationship management). As well as dedicated applications, text analytics capabilities are embedded into many other products (contract life cycle management suites, for example).

A surge in the volume of volume of textual data, especially from sources other than traditional “documents” (such as instant messages and automatically extracted metadata) has fueled the evolution of text analytics. Another strong driver is the desire to complement insights gleaned from analysis of structured numerical data with text-based facts for more robust predictive modelling.

Text analytics is a proven technology that is well adopted, albeit in multiple guises. However, several factors hinder the emergence of more pervasive, easy-to-use business solutions for text analytics. The technology is still maturing, and differentiation between the many overlapping vendors is too nuanced for those organization without in-house expertise. Although easier to use, it is still challenging to incorporate solutions into an organization’s wider digital platform, given the diversity of use cases and specialist skills needed to utilize and gain benefit.

With scope for further evolution, notably the increasing use of machine learning to process text, its current position reflects steady progress up the Slope of Enlightenment.

User Advice: Text analytics is a natural language technology and a form of artificial intelligence (AI). It is therefore important to position it as such.

Given this context:

- Identify and prioritize use cases that text analytics can address.
- Review the text analytics market to acquaint yourself with its vendors, products and capabilities.
- Start with text analytics applications that are provided as prepackaged products designed for nontechnical business users to administer for well-established use cases. These could include voice of the customer (VoC) or employee (VoE).
- Select products based on how well they suit specific business scenarios, and be clear when identifying these.
- Engage with business and analytics leaders to identify relevant initiatives and activities elsewhere in the organization, and especially those involving the use of unstructured data for analytical purposes.
- Look for the ability to integrate with other applications that use unstructured data, such as content services or conversational agents.
- With more use cases and a need to ingrate text analytics into your wider digital business platform, consider text analytics platforms or components.
- Assess references from companies of a similar size, or demand comprehensive proofs of concept from vendors where references are unavailable or ill-matched.

- Allow a realistic lead time to recruit text analytics talent. If the requisite skills are in short supply within the team, consider working with a third-party analytics service provider that offers text analytics capabilities.

Business Impact: In many use cases, text analytics, when combined with various other analytic capabilities, may be of significant benefit to an organization in the following areas:

- Preprocessing unstructured data for analysis (for example, ingesting data from forms captured via OCR for onward processing).
- Automated document matching and classification (analyzing documents and matching metadata to them from a controlled vocabulary).
- Discovery and insight (indexing reports in preparation for natural language question and answering).
- Sentiment (analyzing notes, social medical, or transcripts to identify the author's attitude about a subject).

Use different combinations of technologies for different business use cases:

- Healthcare — medical records analysis by mapping key medicate terms into a graph for analysis.
- Insurance — identifying fraudulent claims by analyzing the narratives and identifying common individuals across claims.
- Finance — gain insights on investments by monitoring public information sources and social media.
- Legal — supporting contract review by extracting key terms and obligations from complex contracts.
- Retail — identifying fraud patterns by analyzing warranty claims.
- Marketing — monitoring brand loyalty and sentiment by analyzing social media feeds and customer feedback.
- Law enforcement — forensic analysis of a body of documents by identifying key subjects and dates, and developing a chain of events.
- Digital publishing — Identifying related articles and developing a summary relevant to an article in progress.

Benefit Rating: Moderate

Market Penetration: 20% to 50% of target audience

Maturity: Early mainstream

Sample Vendors: Amenity Analytics; Cambridge Semantics; Clarabridge; Digital Reasoning; IBM; KNIME; Lexalytics; Megaputer; OdinText; SAS

Recommended Reading: "Artificial Intelligence Primer for 2019"

"Market Guide for Text Analytics"

"Toolkit: Text Analytics Vendors"

"Four Data Preparation Challenges for Text Analytics"

"How Chief Data Officers Can Succeed by Driving Analytic Value"

"Understanding Your Customers By Using Text Analytics and Natural Language Processing"

Entering the Plateau

Data and Analytics Services

Analysis By: Jorgen Heizenberg

Definition: Data and analytics services are the consulting, implementation and managed services for decision support, analytics (including data science and machine learning) and data management capabilities that support an organization's fact-based decision making and enable digital business. These services deliver analytics and business intelligence solutions focusing on business use-cases and outcomes, data governance, data management and master data management solutions focusing on data management infrastructure and governance.

Position and Adoption Speed Justification: Data and analytics services today represent a very mature set of services and solutions for improved measurement and actions. These services are generally well-established, although some areas of innovation (like Machine Learning) still exist, and there are many service providers active in this market. Client adoption levels are high. Enterprises increasingly expect data and analytics services to drive organizational performance and guide digital business. Data and analytics service providers need to master new skills to deal with this changing demand as well as with (new) technologies like AI and data sources like the IoT. As skilled resources are universally in short supply, data and analytics service providers are swiftly moving toward an "asset-based consulting" model where IP assets and automation are used to augment existing insight and expertise for particular vertical industries, or to provide analytics insight to address complex problems. IP assets range from reusable code, process maps, planning tools, impact and readiness assessment frameworks, transformation frameworks, diagnostic tools, and methodologies, to data science, preconfigured solutions and platform-based business solutions. Automation ranges from basic macros and scripts to full-fledged AI, cognitive computing and machine learning.

User Advice: Data and analytics leaders — including chief data officers, chief analytics officers, or heads of business intelligence, analytics, or data management — need to help their organizations use the most impactful data so that they can analyze, collaborate and make better decisions. In the next six months, they should decide on the need to hire external analytics service providers. This should be based on the type of initiative such as data and analytics strategy, data management or data governance or analytics programs. They should prioritize requirements for data and analytics skills, industry experience and technology toolkits. Finally, they need to identify the types of intelligent automation and self-learning required in the process and workflow. However, the primary focus should be on the business use-cases supported by the data foundation and analytics capability.

Business Impact: Enterprises transforming from being process-driven to data-driven as they move to digital business and continue to use information as an asset will see the greatest impact from data and analytics services. Any organization moving to a more-fact-based approach for decisions will need a life cycle of planning, building, managing and optimizing data and analytics solutions through services. Additionally, organizations that start innovating with AI and machine learning technologies will favor automated and self-learning approaches, and will expect improved accuracy, trustworthiness and speed to solution.

Benefit Rating: High

Market Penetration: 20% to 50% of target audience

Maturity: Mature mainstream

Sample Vendors: Accenture; Capgemini; Cognizant; Deloitte; EY; IBM Global Business Services; KPMG; PwC; TCS; Wipro

Recommended Reading: "Magic Quadrant for Data and Analytics Service Providers, Worldwide"

"Critical Capabilities for Data and Analytics Service Providers, Worldwide"

"Market Guide for Data and Analytics Service Providers"

"How Chief Data Officers Can Scale the Value of Data and Analytics by Working With External Service Providers"

Visual Data Discovery

Analysis By: Kurt Schlegel

Definition: Visual data discovery is a BI platform architectural style that blends data from multiple sources into a proprietary in-memory store that is tightly coupled with an interactive visualization layer. It is a defining feature of mainstream modern analytics and BI platforms. It contrasts with the traditional BI platform that relies on a more modular, semantic and model-centric architecture dependent on three distinct technologies to integrate, store and present data.

Position and Adoption Speed Justification: Over the last ten years, the market has dramatically shifted in favor of the visual data discovery architecture. This shift is mostly driven by new consumers, commonly business analysts, in the lines of business. The vast majority of new analytics and BI deployments leverage a visual data discovery architecture over the traditional BI platform architecture. The rapid adoption has been accelerated by a viral sales model that makes it easy for individuals to try visual data discovery to build analytic views and easily share them more broadly across their organizations. As a result of this buyer interest, virtually all the traditional BI platform vendors have refocused on visual data discovery as a key component of their go-to-market offerings. The visual data discovery architecture, while empowering, is also quite manual, and will see increasing competition from the augmented analytics architecture.

User Advice: Users clearly want the ease of use and self-service that visual data discovery provides. Analytics and BI leaders should provision this capability as a key aspect of their technical architectures. They should also recognize that visual data discovery tools do not offer all of the features of traditional BI platforms, particularly with respect to governance and manageability. An effort should be made to provide manual processes to more closely manage end-user-created analytic content. Choosing between visual and augmented analytics is a debate between “eyeballs and algorithms.” Our recommendation is that analytics programs need both. You should use augmented analytics to automate the analysis process, and then communicate those findings using visual data discovery.

Business Impact: Typically, visual data discovery is used for more agile rapid prototyping, making it possible for end users to blend datasets together quickly. It provides users with a more unfettered drilling experience. Therefore, visual data discovery not only offers more self-service, but also offers deeper diagnostic analytic capability to most users and organizations. The rise of data preparation technology is making visual data discovery more relevant for larger and more complex and disparate data sources and enterprise use cases.

Benefit Rating: Low

Market Penetration: More than 50% of target audience

Maturity: Mature mainstream

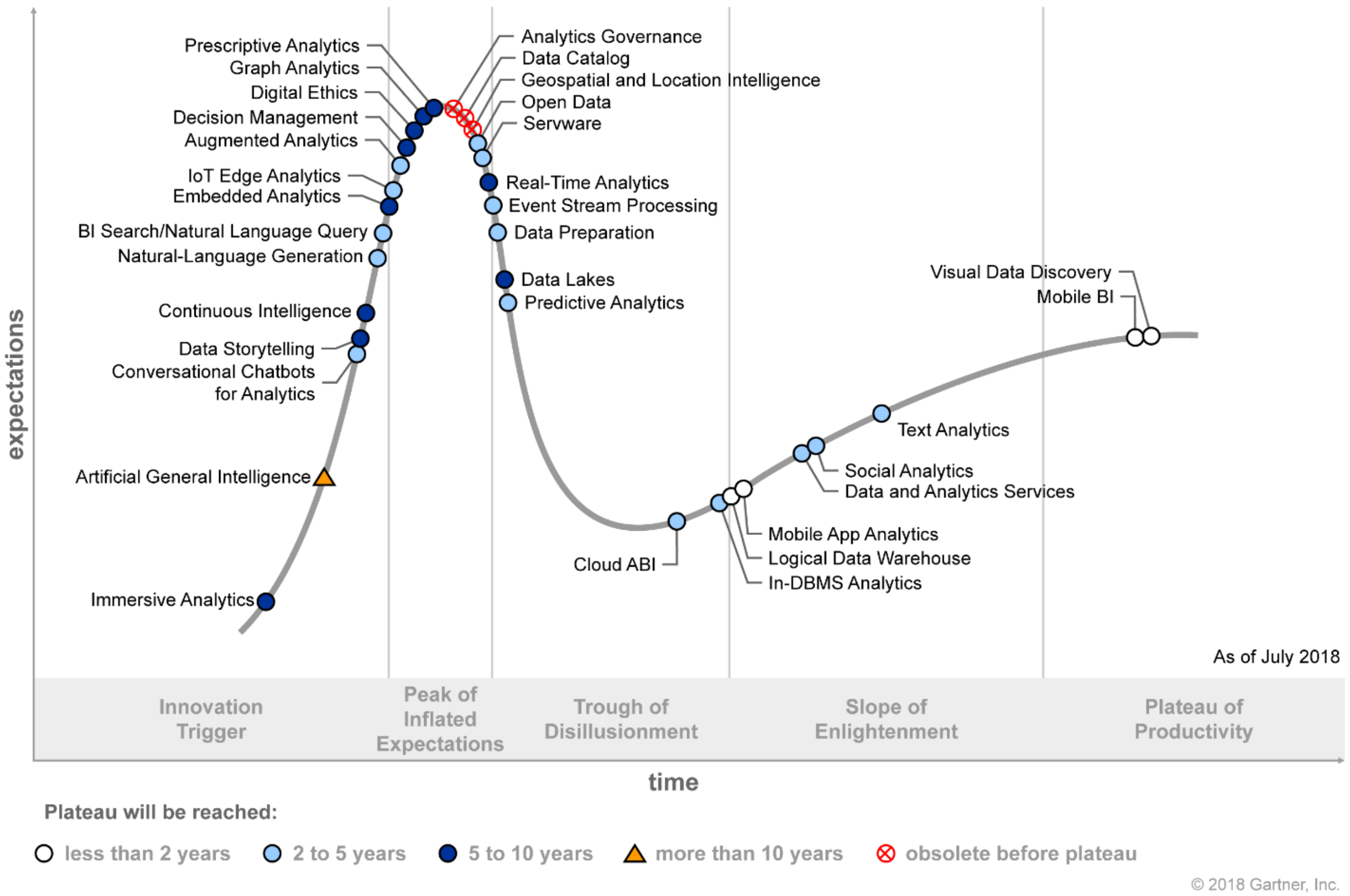
Sample Vendors: Microsoft; Qlik; Tableau Software; TIBCO Software (Spotfire)

Recommended Reading: “Critical Capabilities for Analytics and Business Intelligence Platforms”

“Magic Quadrant for Analytics and Business Intelligence Platforms”

Appendixes

Figure 3. Hype Cycle for Business Intelligence, 2018



Hype Cycle Phases, Benefit Ratings and Maturity Levels

Table 1: Hype Cycle Phases

Phase	Definition
Innovation Trigger	A breakthrough, public demonstration, product launch or other event generates significant press and industry interest.
Peak of Inflated Expectations	During this phase of overenthusiasm and unrealistic projections, a flurry of well-publicized activity by technology leaders results in some successes, but more failures, as the technology is pushed to its limits. The only enterprises making money are conference organizers and magazine publishers.
Trough of Disillusionment	Because the technology does not live up to its overinflated expectations, it rapidly becomes unfashionable. Media interest wanes, except for a few cautionary tales.
Slope of Enlightenment	Focused experimentation and solid hard work by an increasingly diverse range of organizations lead to a true understanding of the technology's applicability, risks and benefits. Commercial off-the-shelf methodologies and tools ease the development process.

Phase	Definition
Plateau of Productivity	The real-world benefits of the technology are demonstrated and accepted. Tools and methodologies are increasingly stable as they enter their second and third generations. Growing numbers of organizations feel comfortable with the reduced level of risk; the rapid growth phase of adoption begins. Approximately 20% of the technology's target audience has adopted or is adopting the technology as it enters this phase.
Years to Mainstream Adoption	The time required for the technology to reach the Plateau of Productivity.

Source: Gartner (July 2019)

Table 2: Benefit Ratings

Benefit Rating	Definition
Transformational	Enables new ways of doing business across industries that will result in major shifts in industry dynamics.
High	Enables new ways of performing horizontal or vertical processes that will result in significantly increased revenue or cost savings for an enterprise.
Moderate	Provides incremental improvements to established processes that will result in increased revenue or cost savings for an enterprise.
Low	Slightly improves processes (for example, improved user experience) that will be difficult to translate into increased revenue or cost savings.

Source: Gartner (July 2019)

Table 3: Maturity Levels

Maturity Level	Status	Products/Vendors
Embryonic	▪ In labs	▪ None

Maturity Level	Status	Products/Vendors
Emerging	■ Commercialization by vendors ■ Pilots and deployments by industry leaders	■ First generation ■ High price ■ Much customization
Adolescent	■ Maturing technology capabilities and process understanding ■ Uptake beyond early adopters	■ Second generation ■ Less customization
Early mainstream	■ Proven technology ■ Vendors, technology and adoption rapidly evolving	■ Third generation ■ More out-of-box methodologies
Mature mainstream	■ Robust technology ■ Not much evolution in vendors or technology	■ Several dominant vendors
Legacy	■ Not appropriate for new developments ■ Cost of migration constrains replacement	■ Maintenance revenue focus
Obsolete	■ Rarely used	■ Used/resale market only

Source: Gartner (July 2019)

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Hype Cycle for Business Intelligence and Analytics, 2014 - 31 July 2014

Hype Cycle for Business Intelligence and Analytics, 2013 - 31 July 2013

Hype Cycle for Business Intelligence, 2012 - 13 August 2012

Hype Cycle for Business Intelligence, 2011 - 12 August 2011

Hype Cycle for Business Intelligence, 2010 - 16 August 2010

Hype Cycle for Business Intelligence and Performance Management, 2009 - 27 July 2009

Hype Cycle for Business Intelligence and Performance Management, 2008 - 22 July 2008

Hype Cycle for Business Intelligence and Performance Management, 2007 - 23 July 2007

Hype Cycle for Business Intelligence and Corporate Performance Management, 2006 - 14 July 2006

Recommended by the Authors

Understanding Gartner's Hype Cycles

Augmented Analytics Is the Future of Data and Analytics

Technology Insight for Modern Analytics and Business Intelligence Platforms

Predicts 2019: Analytics and BI Strategy

Recommended For You

Critical Capabilities for Analytics and Business Intelligence Platforms

Magic Quadrant for Analytics and Business Intelligence Platforms

Other Vendors to Consider for Modern Analytics and BI

Predicts 2020: Analytics and Business Intelligence Strategy

Evolving From Spreadsheets in the Age of Modern Analytics and Business Intelligence objectivity. Its research is produced independently by its research organization without input or influence from any third party. For further information, see "Guiding Principles on Independence and Objectivity."