Hype Cycle for Analytics and Business Intelligence, 2021

Published 29 July 2021 - ID G00747544 - 128 min read

By Analyst(s): Austin Kronz, Peter Krensky

Initiatives: Analytics, BI and Data Science Solutions

This Hype Cycle will help data and analytics leaders evaluate the maturity of innovations across the ABI space. Key trends include consumer-focused augmented analytics, composability of D&A ecosystems, and the governance and education required to execute a variety of analytics at scale.

Additional Perspectives

- Summary Translation: Hype Cycle for Analytics and Business Intelligence, 2021 (23 August 2021)

Analysis

What You Need to Know

This document was revised on 6 August 2021. The document you are viewing is the corrected version. For more information, see the Corrections page on gartner.com.

With data at the core of all digital businesses, analytics and business intelligence (ABI) remains a top priority for IT and business leaders. Innovations in analytics technology have increased the automation of various analytics tasks, augmenting the analyst persona. Many data and analytics (D&A) vendors moved quickly to add capabilities that augment the analyst. However, they are under pressure to sustain such technical differentiation for a prolonged period — something that is increasingly difficult due to the frequency of new product releases in cloud-first development environments.

The next wave of innovation will target the augmented consumer (see Top Trends in Data and Analytics for 2021: The Rise of the Augmented Consumer). Extending augmentation beyond the analyst and directly to the analytics consumer requires more proactive, automated and contextualized insights, as well as intuitive and enhanced user interfaces. As more users analyze more data, organizations must focus efforts and investments equally on challenges relating to governance, data literacy, and education about the appropriate and ethical use of data.

In addition to this Hype Cycle, D&A leaders should consult the following Hype Cycles in adjacent areas:

- Hype Cycle for Data Science and Machine Learning, 2021
- Hype Cycle for Data and Analytics Governance and Master Data Management, 2021
- Hype Cycle for Artificial Intelligence, 2021
- Hype Cycle for Enterprise Information Management, 2021
- Hype Cycle for Customer Experience Analytics, 2021

Together, these six Hype Cycles analyze the elements required for D&A leaders to form a holistic view of the data and analytics ecosystem.

The Hype Cycle

The ABI space overlaps and collides with other areas, such as data science and machine learning (DSML) and data management. This collision of technologies and practices from peripheral domains extends what users can do within an ABI platform. However, it requires an emphasis on how these D&A tools and business applications can be composed together to maximize value for a wider audience. Due to the rapid pace of development cycles in a cloud-first world, many innovations will progress very quickly through the Hype Cycle. The majority of innovations in this Hype Cycle are likely to reach the Plateau of Productivity in five years or less. Innovation in this space continues to accelerate because data and analytics is a top priority for organizations.

New Entrants

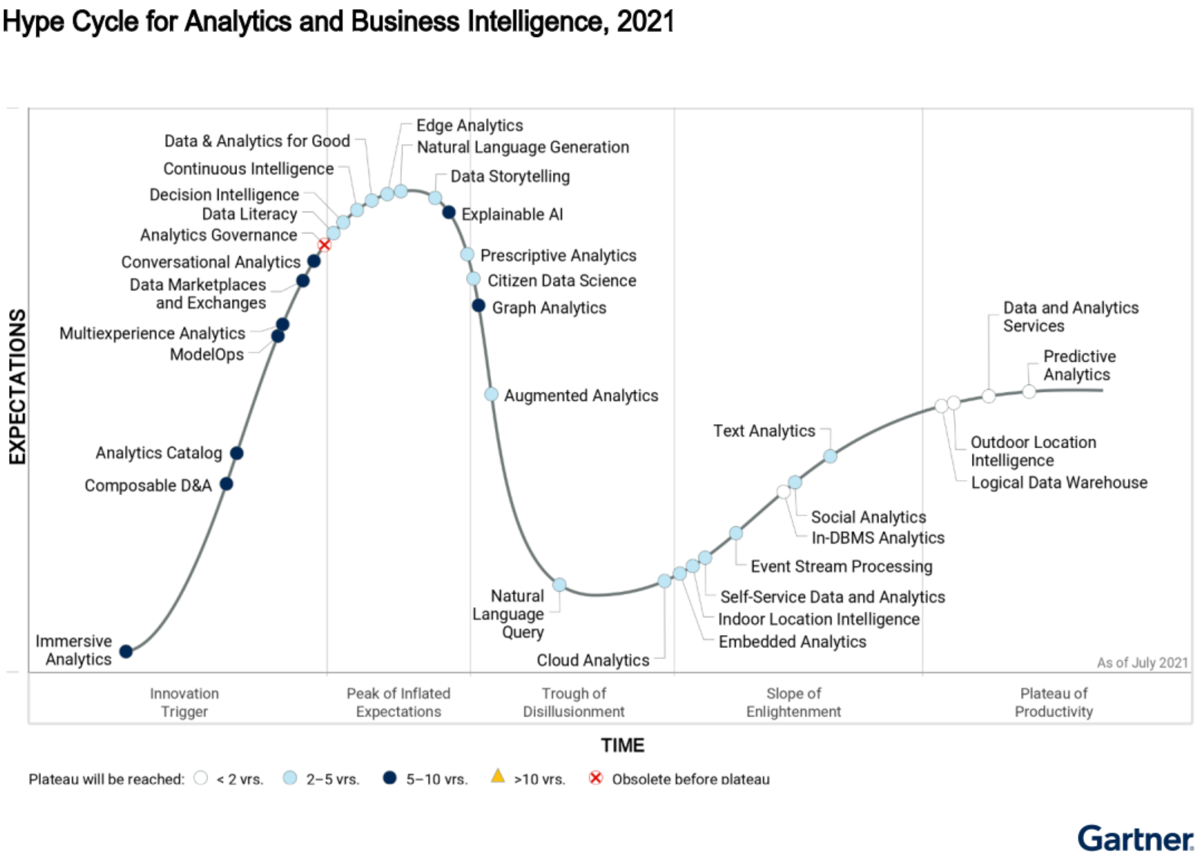
- **Composable D&A:** A Gartner top trend in data and analytics, [1] composable D&A utilizes container- or business-microservices-based architecture and data fabric to assemble flexible, modular and consumer-friendly D&A and artificial intelligence (AI) capabilities from existing assets. This enables more freedom of tooling for insight creators and fosters widespread analytical activity and collaboration.
- **Citizen Data Science:** Although not a new concept, citizen data science is new to this Hype Cycle. Citizen data science helps unlock new insights (typically predictive) beyond use of basic descriptive and diagnostic capabilities, enabling democratization of analytics capabilities as well as an upskilling path and new opportunities for business analysts and developers.
- **Self-Service Data and Analytics:** Self-service D&A enables organizations to create analytics prototypes and pilot them faster, compared with relying solely on IT for analytics projects.
- **Data Marketplaces and Exchanges:** Marketplaces and exchanges remove barriers to the acquisition of third-party data in support of increasingly data-driven business outcomes and underlying models. Adoption of data marketplaces and exchanges remains in the early phases, but providers are bringing together stakeholders with mutual interests in diverse third-party asset selection, simplified data access/integration, simplified procurement, and reduced operating and transaction costs.

- **ModelOps:** Model operationalization (ModelOps) is primarily focused on the end-to-end governance and life cycle management of all analytics, artificial intelligence and decision models (including analytical models and models based on machine learning, knowledge graphs, rules, optimization, linguistics, agents and others).

Name Changes

- **Analytics Governance (formerly Analytics Stewardship):** “Governance” is how this concept is commonly referred to, and governance also represents a broader set of functions, including stewardship.
- **Data and Analytics for Good (formerly Data for Good):** Data and data-driven insights can be made accessible to generate a positive social impact.
- **Conversational Analytics (formerly Conversational Chatbot for Analytics):** “Conversational” implies the back-and-forth nature of a chatbot experience.

Figure 1: Hype Cycle for Analytics and Business Intelligence, 2021



Source: Gartner (July 2021)

Downloadable graphic: Hype Cycle for Analytics and Business Intelligence, 2021

The Priority Matrix

To help organizations prioritize investments in relation to their level of impact, we provide a Priority Matrix. 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 ROI are also important. The Priority Matrix shows the degree of benefit attainable from an innovation, relative to its progression along the Hype Cycle.

Innovations of transformational benefit have a demonstrable, powerful impact on business models/results. Composable D&A and decision intelligence offer transformational potential. Composability enables organizations to assemble custom-made, consumer-focused combinations of analytics services for highly personalized insights and experiences. Decision intelligence aims to improve the impact of business processes by materially enhancing the sustainability of organizations' decision models based on the power of their relevance, the quality of their transparency and the strength of their resilience. Thus, decisions become more transparent and auditable.

Innovations of high benefit are less likely to change an organization's business model, but they will have a significant impact on its ABI program. The majority of high-benefit innovations will progress toward the Plateau of Productivity over the next two to five years. Fundamentals for successful ABI programs, such as self-service D&A, are just breaking through the Trough of Disillusionment, while data literacy and data storytelling continue to generate hype and will experience periods of inflated expectations and disillusionment before achieving consistent productivity.

Although it may take five to 10 years for them to achieve mainstream adoption, innovations such as composable D&A, data marketplaces and exchanges, graph analytics, and ModelOps will greatly benefit ABI programs. Innovations in this category increase the personalization, data access, depth and breadth of ABI initiatives, but require long-term investment to deliver value and trusted insights.

Table 1: Priority Matrix for Analytics and Business Intelligence, 2021

(Enlarged table in Appendix)

Benefit	*Years to Mainstream Adoption*			
↓	*Less Than 2 Years* ↓	*2 - 5 Years* ↓	*5 - 10 Years* ↓	*More Than 10 Years* ↓
Transformational		Augmented Analytics Citizen Data Science Continuous Intelligence Decision Intelligence Event Stream Processing	Composable D&A	
High	Data and Analytics Services In-DBMS Analytics Logical Data Warehouse Outdoor Location Intelligence Predictive Analytics	Data Literacy Data Storytelling Edge Analytics Embedded Analytics Indoor Location Intelligence Natural Language Generation Prescriptive Analytics Self-Service Data and Analytics	Conversational Analytics Data Marketplaces and Exchanges Explainable AI Graph Analytics ModelOps	
Moderate		Cloud Analytics Data & Analytics for Good Natural Language Query Social Analytics Text Analytics	Analytics Catalog Immersive Analytics Multiexperience Analytics	
Low				

Source: Gartner (July 2021)

Off the Hype Cycle

- **D&A Governance** can be found in other Hype Cycles and is still relevant in all aspects of data and analytics. Analytics Governance, as included in this Hype Cycle, is a more specific and appropriate innovation for this audience.
- **Data Catalog** has been renamed to Augmented Data Cataloging and Metadata Management, and is included in the more appropriate Hype Cycle for Data and Analytics Governance and Master Data Management, 2021.
- **Digital Ethics** can be found in other Hype Cycles, such as the Hype Cycle for Artificial Intelligence, 2021, and is of greater relevance for that audience.
- **Analytics Stewardship** has been renamed to Analytics Governance.
- **Data for Good** has been renamed to Data & Analytics for Good.
- **Conversational Chatbot for Analytics** has been renamed to Conversational Analytics.

On the Rise

Immersive Analytics

Analysis By: Marty Resnick

Benefit Rating: Moderate

Market Penetration: Less than 1% of target audience

Maturity: Emerging

Definition:

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

Why This Is Important

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. 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.

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. Additional opportunities exist for operational workers, engineers and scientists to use immersive analytics, since it visualizes the data in the context of the consumer's world.

Drivers

Organizations are at the early stage with immersive analytics, moving from experimentation and POC to limited deployment.

There are four main drivers for immersive analytics:

- **Engagement and immersion:** Technological immersion relates to the technologies used in VR, AR and MR to immerse the user completely in a virtual world or one blended with the physical world. Engagement presence is a sensory experience in which the users feel and behave like they are indeed present in the virtual world, temporarily unaware that they are inhabiting a computer-mediated environment.
- **Data-driven storytelling:** This prompts a feeling of being closely connected to the data story and its intended message. It elicits an emotional reaction to the message. This emotional reaction can be a positive or negative one, including anger or sadness about the depicted content, or a feeling of surprise and joy about the data. It also evokes an urge to deeply explore and “get lost” in the data story, driving deep engagement or engrossment with the components of the data story.
- **Collaboration:** Immersive head-mounted-displays can be used to allow analysts working at different locations to come together in the same virtual space to jointly explore complex datasets. Users can record a voice message and annotations, along with their virtual avatar body movements and gestures for later playback. Casual information may be visualized in a public setting (e.g., showing bus timetable information, social networks or photo collections). Synchronous collaboration can occur between people in the same location and a remote location (e.g., education).
- **Dealing with vast amounts of often-disconnected data:** The amount of data that accompanies these types of use cases, as well as graph-relationship-based analytics, is huge. Data is often too vast for humans to comprehend, let alone act on, using 2D screens. Immersive analytics could prove ideal for organizations implementing Internet of Things initiatives, given the massive amount of sensor data.

Obstacles

- 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.
- The ability to create these visualizations internally or as part of a data analytics platform is very limited, thus making immersive analytics challenging to create and maintain long term.

- Cost of content creation is a barrier, as well as the cost of the hardware to view the experiences.

User Recommendations

- Use a combination of augmented and immersive analytics to mitigate limited views of data.
- Review the roadmaps and capabilities of your existing analytics vendors and those you 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 experiences (e.g., visualization, audio, haptic).
- 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.
- Pilot the use of immersive analytics with business users to get feedback on the pros and cons, and identify specific use cases where it can improve productivity and/or make it easier to explore and analyze data.

Sample Vendors

Slanted Theory; Virtualitics

Composable D&A

Analysis By: Julian Sun, Carlie Idoine, Erick Brethenoux

Benefit Rating: Transformational

Market Penetration: Less than 1% of target audience

Maturity: Embryonic

Definition:

Composable data and analytics (D&A) utilizes container- or business-microservices-based architecture and data fabric to assemble flexible, modular and consumer-friendly D&A and AI capabilities from existing assets. This transforms monolithic data management and analytics applications into assemblies of D&A and AI or other application building blocks. This is achieved via composition technologies enabled by low- and no-code capabilities, supporting adaptive and intelligent decision making.

Why This Is Important

Investment in D&A is usually separate from investment in business applications, making it difficult to generate combined business outcomes. Organizations are looking for flexibility in assembly/reassembly of D&A capabilities, enabling them to blend more insights and references into actions. In the aftermath of global disruption, time to insight and agility have become top requirements. Modular D&A capabilities would enable a more proactive and quicker application delivery.

Business Impact

The transition from monolithic D&A applications to composable D&A capabilities can be used along with application development to assemble intelligent decision-making solutions. The composition is a collaboration between D&A and application teams. The focus of collaboration will transition from technology integrations to business problem solving. Organizations can create advanced analytics capabilities by composing the best capabilities from different vendors, rather than using them separately.

Drivers

- Container- or microservices-based ABI and DS/ML platforms with improved APIs enable the assembly of analytics applications in a more flexible way as compared to custom code-based solutions.
- For most organizations, AI is still at the piloting stage, but BI has been in production for years. Organizations can use composition to connect BI to AI, extending BI capabilities and empowering users with a comprehensive, tailored, even personalized solution without having to use different applications.
- Assemble descriptive, diagnostic, predictive and prescriptive analytics capabilities dynamically to generate insights along with the decision-making process. Use analytics to inform decision making and drive effective actions in a more connected, continuous and contextual way.
- More business technologies emerge in the organizations and they will request more capabilities. Both data and analytics and software development teams will need composable data and analytics to enable business technologies.
- As more data and analytics are integrated into digital platforms, the traditional embedded analytics will need more modular capabilities to be assembled and reassembled for faster delivery.
- Embedded analytics are usually implemented by IT, and dashboarding and reporting are the major purposes. Business users can use low- or no-code capabilities to compose more capabilities, such as interactive visualization and predictive modeling, enriching more comprehensive embedded analytics.
- Cloud-based marketplaces are becoming an effective channel for organizations to distribute and share analytics applications, and composable D&A enables them to easily find the required components and add value to their applications by infusing analytics.

Obstacles

- New technology and data have been the key drivers to evolve an analytics platform, resulting in less of a connection with business outcomes. Organizations will use a top-down approach, focusing on which data and analytic capabilities they need to plan the composable data and analytics.
- Application development team and data and analytics teams have not collaborated closely before. Composable data and analytics would require more involvement from the application development side including applying the XOps practice to maximize its value.
- Today's ABI and DS/ML markets are not zero-sum games. No single vendor or tool offers all functions at the same level. It is unrealistic to implement a full D&A stack all at once, so many companies do so in stages. The composability of the existing products is not mature enough without technology partnership.

User Recommendations

- Improve decision making and business impact of data and analytics by incorporating and assembling modular, reusable D&A capabilities.
- Leverage composable analytics to drive innovation by incorporating advanced DS/ML capabilities into analytics applications.
- Exploit opportunities to add analytics capabilities to applications by building a joint team of application developers and business analysts with ongoing collaboration. Rethink organization, processes and skills to support agile assembly and reassembly of analytics services.
- Pilot composable analytics in the cloud, establishing an analytics marketplace to drive and support collaboration and sharing.

Sample Vendors

GoodData; Logi Analytics; Oracle; Sisense; Yellowfin

Gartner Recommended Reading

Composable Analytics Shapes the Future of Analytics Applications

The Future of Data and Analytics: Reengineering the Decision, 2025

Use Gartner's Reference Model to Deliver Intelligent Composable Business Applications

Analytics Catalog

Analysis By: James Richardson

Benefit Rating: Moderate

Market Penetration: 1% to 5% of target audience

Maturity: Emerging

Definition:

Analytics catalogs apply portal-like curation and collaboration functions to analytics and BI (A&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.

Why This Is Important

Many large organizations use multiple A&BI technologies to support a wide range of analytics processes, and portfolio deployments are commonplace. As such, there is a need to help business decision makers get to the right content from more than one underlying technology. Analytics catalogs address a real pain point impacting organizations using multiple A&BI tools by giving business users a single point of access.

Business Impact

- Having a range of reports, dashboards, data visualizations or datasets is pointless if end users struggle to find or navigate them. Analytics catalogs help decision makers find the analytics content they need.
- Analytics catalogs can drive wider adoption of A&BI tools and help organizations become more data-centric.
- Analytics catalogs deliver a one-stop shop and allow internal users to find content, and rank and review its relevance and business value. This helps D&A leaders focus their efforts.

Drivers

- 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 commercial off-the-shelf (COTS) application.

- 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. Because of historic vendor relationships or best-of-breed preference in sourcing, most organizations will continue to use more than one analytics technology.

- Some of these products go beyond simply identifying content at the report or dashboard level, decomposing content down to individual charts or tables and maintaining full interactivity (for example, via sorting, filtering or revisualization). Organizations that want to compose analytics applications drawing together granular content from a variety of BI tools may select an analytics catalog for this capability.

- Organizations that are looking to migrate from an old, possibly on-premises BI platform to a newer cloud-based analytics technology need to know what content to migrate (and what not to). An analytics catalog provides visibility into usage patterns that can help this use case.

Obstacles

- Lack of knowledge: There is little hype around these tools but a clear need for them in many organizations. A reference customer Gartner interviewed said they were surprised that analytics catalogs were so little known and used.
- Lack of support from large vendors: The reason analytics catalogs are not a well-known option may be because vendors of A&BI platforms would rather their customers not use competing products, and thus, don't promote this functionality.
- Aspiration to single vendor standardization: If you're aiming for a single vendor solution, then a portal-like tool is of less relevance. However, in many cases this is not a realistic aim. No single vendor or tool offers everything at the same level of functionality, departments may demand specific analytics tools, new capabilities may become available that are not offered by incumbent software providers and M&A activity often brings different, nonstandard tools into the organization.

User Recommendations

Data and analytics leaders should:

- Run a POC to evaluate analytics catalogs and explore the benefit that a managed single access point for A&BI content could provide to users.
- Compare the functionality and cost of any custom-built BI portals versus that offered by commercial analytics catalog tools.
- Evaluate how these tools could help them 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.

Sample Vendors

Digital Hive; Enquero; Metric Insights; Visual BI; ZENOPTICS

Gartner Recommended Reading

Cool Vendors in Analytics and Data Science

Cool Vendors in Analytics

How to Manage a Portfolio of Analytics, Business Intelligence and Data Science Tools

ModelOps

Analysis By: Farhan Choudhary, Erick Brethenoux, Soyeb Barot

Benefit Rating: High

Market Penetration: 1% to 5% of target audience

Maturity: Emerging

Definition:

Model operationalization (ModelOps) is primarily focused on the end-to-end governance and life cycle management of all analytics, AI and decision models (including analytical models and models based on machine learning, knowledge graphs, rules, optimization, linguistics, agents and others).

Why This Is Important

As per Gartner's 2019 AI in Organizations survey, machine learning was the most leveraged AI technique, but not the only one. Organizations across all maturity levels rely on a variety of analytics and AI techniques, such as analytical, graph, agent-based, physical, simulation and ML models. This is where ModelOps helps — with operationalization agnosticity. Although MLOps primarily focuses on monitoring and governance of machine learning models, ModelOps assists in the operationalization and governance of all analytics, decision and AI models.

Business Impact

- Lays down the foundation for management of various knowledge representation models, reasoning capabilities and composite integration
- Creates the ability to manage decision models, integrating multiple analytics techniques for robust decision making
- Ensures collaboration among a wider business, development and deployment community, and the ability to correlate analytics model outcomes with business KPIs
- DataOps practices and ModelOps are key to addressing the data and models overlay/dependencies and ensure frictionless transfer of artifacts from one stage to another

Drivers

- As the number of projects at organizations increase, and as projects become more complicated, they will have to manage different types of analytics, AI and decision models that require different operationalization and governance procedures, especially if built from scratch.
- Organizations want to be more agile and responsive to changes within their analytics and AI pipelines, not just with models but also with data, application and infrastructure.
- The operationalization of aspects of ML models is not new, but it is in its early stages. However, with ModelOps, the functionalities provided by MLOps are extended to other non-ML models.
- ModelOps provides an appropriate abstraction layer by separating the responsibilities across various teams for how models (including analytics, machine learning, physical, simulation, symbolic and more) are built, tested, deployed and monitored across different environments (for example, development, test and production). This enables better productivity and lowers failure rates.
- There's a need to create resilient and adaptive systems that use a combination of various analytical techniques for decision support, augmentation and automation.
- There are wider risk management concerns with different models — drift, bias, explainability and integrity — which ModelOps helps address.

Obstacles

- Organizations using different types of models in production often don't realize that, for some kinds of analytics, decision and AI models (rule-based, agent-based, graph or simulation models) end-to-end governance and management capabilities can be expanded further.
- Not all analytical techniques currently benefit from mature operationalization methods. Because the spotlight has been on ML techniques, MLOps benefits from a more mature understanding, but others, such as agent-based modeling, require more attention.
- The lack of knowledge relevant to leveraging multiple analytics and AI techniques could prevent organizations from considering the techniques particularly suited to solving specific problems.
- Organizations that are siloed reinforce the practice and even separate their analytics model development from their AI model development for what is essentially the same process. This leads to redundancy in effort, or can, and reinforces the silos.

User Recommendations

- Leverage different analytics and AI techniques to increase the success rate of data and analytics initiatives.
- Utilize DevOps best practices across data, models and applications to ensure transition, reduce friction and increase value generation (e.g., using agile and lean).
- Extend the skills of ML experts, or recruit/upskill additional AI experts, to also cover graph analytics, optimization or other required techniques for composite AI. In the case of rules and heuristics, skills for knowledge elicitation and knowledge engineering should also be available.
- Establish a culture that encourages collaboration between development and deployment teams and empower them to make decisions to automate, scale and bring stability to the analytics pipeline.
- Optimize the adaptability and efficiency of your AI projects by considering a composite AI approach — integrating various AI techniques to solve business problems.

Sample Vendors

Algorithmia; Hewlett Packard Enterprise (HPE); IBM; ModelOp; Modzy; ONE LOGIC; SAS; Veritone

Gartner Recommended Reading

Top 5 Priorities for Managing AI Risk Within Gartner's MOST Framework

Innovation Insight for ModelOps

Demystifying XOps: DataOps, MLOps, ModelOps, AIOps and Platform Ops for AI

Multiexperience Analytics

Analysis By: Austin Kronz

Benefit Rating: Moderate

Market Penetration: 1% to 5% of target audience

Maturity: Emerging

Definition:

Mutliexperience analytics is the alignment of user interfaces, interaction modalities and analytic capabilities that optimize a user's experience of analytics content consumption for a given decision-making process. The increase in possible combinations of approaches is due to advancements in technologies such as augmented analytics capabilities and data storytelling.

Why This Is Important

Much like the customized user experiences we are used to in our day-to-day interactions with technology, consumer-oriented analytics experiences will be needed to drive adoption of data-driven decisions. Organizations must be able to deliver the most relevant, contextualized and consumable analytics outputs possible. This requires tapping into the unique intersection of various devices, interaction modalities, and analytics capabilities that can augment users' ability to consume insights.

Business Impact

Transitioning from static analytics outputs to more dynamic contextualized insights, embedded or automated, means analytics can be delivered with increased relevance closer to the point of decision. Aligning analytics capabilities with their optimal interface and consumption modality will impact our approach of measuring analytics and BI adoption. Quantifying adoption will need to shift from identifying how many users leverage a tool to how many people consult data when making a decision.

Drivers

- Multiexperience is closely coupled to advancements in both hardware and software — hardware in the form of interfaces such as desktops, mobile devices, wearable devices or smart speakers, and software in the form of augmented analytics and data storytelling capabilities.
- The various modalities in which we can interact with data (click, touch, voice, chat, etc.) is generally accepted, yet organizations are only scratching the surface when it comes to maximizing the cross section of these interfaces and capabilities. Many organizations are already using embedded forms of analytics, a starting point for multiexperience.
- Because capabilities such as augmented and automated data storytelling are almost entirely enabled by cloud-based architectures, adoption will be accelerated proportionate to organizations' movement to cloud-based data and analytics tools.

Obstacles

- While there are a wide variety of possibilities when it comes to delivering multiexperience analytics to users, the roles and skills needed to compose the various elements together will be an ongoing challenge.
- The time needed, from the already scarce D&A resources, to learn how to maximize the combination of new interaction modalities and analytics capabilities will be in direct competition of time needed for day-to-day analytics requests that many D&A teams are already inundated with.

User Recommendations

- Account for multiexperience approaches to consuming data by aligning the right analytic capability to the right user interface and experience.
- As movement to the cloud continues, avoid simply lifting and shifting the same traditional analytics outputs to a modern platform and instead evaluate where new consumption mechanisms could add value to decision making processes.
- Evaluate, on a regular basis, your existing analytics and BI tools and innovative startups offering new augmented user experiences beyond the predefined dashboard.
- Place analytics capabilities as close to the relevant business decision maker as possible by evaluating when analytics and BI platform capabilities are best embedded in-line with other business applications or workflows.
- Take a data-driven approach to analytics adoption by leveraging the usage data available within today's analytics and BI platforms. If not prebuilt, discuss with vendors the options available to tap into such data.

Gartner Recommended Reading

Multiexperience Will Be the New Normal for Consuming Analytics Content in the Augmented Era

Top 10 Trends in Data and Analytics, 2021: The Augmented Consumer

Maximize the Benefits of Augmented Analytics With a Strategic Action Plan

Data Marketplaces and Exchanges

Analysis By: Eric Hunter, Jim Hare, Lydia Clougherty Jones

Benefit Rating: High

Market Penetration: 5% to 20% of target audience

Maturity: Emerging

Definition:

Data marketplaces and exchanges are ecosystems centered around data assets that provide infrastructure, transactional capabilities and services for participants. Marketplaces support data monetization via one-time or recurring subscription transactions while exchanges prioritize sharing of assets over monetization objectives. Both can incorporate public or private-sector participants and commercial or no-cost assets, such as open data.

Why This Is Important

Public cloud adoption has largely minimized data gravity as the primary barrier to data marketplaces and exchanges as the balance of data has shifted to CSPs in many organizations. Adoption of data marketplaces and exchanges remain in the early phases, but providers are bringing together stakeholders with mutual interests. Participants are attracted to diverse third-party asset selection, simplified data access/integration, simplified procurement, and reduced operating and transaction costs.

Business Impact

- Increase the prevalence of third-party data assets for data science models, data enrichment and line of business operational demands (marketing campaigns, etc.).
- Reduce the complexity, time and cost demands for sourcing third-party data assets.
- Increase data monetization opportunities and market reach via marketplaces.
- Data exchanges reduce the barrier to entry for nonmonetized data sharing.
- Expand the visibility, findability, variety and availability of data products.

Drivers

Marketplaces and exchanges remove barriers to the acquisition of third-party data in support of increasingly data-driven business outcomes and underlying models. They also reduce the exclusivity of specific types of data products through increased competition that will reduce price points for similar data products over the long term. Marketplaces and exchanges continue to increase in adoption through the following drivers:

- Digital business transformation has positioned data products as a key enabler of emerging business outcomes — increasing the demand for third party data, the growing role of business ecosystems, and the growing awareness and need for companies about partnering

- There is increased awareness across both public and private sectors in terms of the value associated with both internal and external data assets and products.

- COVID-19 has driven change across the behavior of many customers, resulting in model accuracy drift for data science models that rely heavily upon first-party customer data for key model features. Third-party data acquired from marketplaces and exchanges has become more attractive as an enabler for remediating these model accuracy issues and in the creation of new model features.

- There is increased adoption of public cloud which has reduced on-premises data gravity limitations that slow the physical movement and integration of data across parties.

- The number of public and private data providers for data marketplaces and exchanges continues to increase — providing both an increased level of specialization and breadth in terms of available third-party data product offerings.

- There is rising awareness of internal and external data sharing benefits through increased virtual work environments, COVID-19-centric use cases and increased enterprise reliance on public cloud.

Obstacles

- Data privacy legislation and risks of sharing data impede the pursuit of monetizing and productizing specific types of data, which reduces participation within data marketplaces and exchanges.

- It is a challenge to have mutually acceptable standards for governance of data-sharing scenarios without a balance of common cause and enlightened self-interest.

- Evolving organizational data ethics and sharing standards can prevent the adoption of third party data and/or creation of third-party data products that drive data marketplaces and exchanges.

- Enterprise procurement processes and public cloud account structures provide friction for lines of business user spend within public cloud data marketplace and ecosystems.

- Absent the specialized capabilities for evaluating relevant data products for a given use case, the volume of available marketplace and exchange data product offerings and lacking metadata can overwhelm buyers evaluating the ability of specific data products for new model features.

User Recommendations

- Promote organizational participation in your marketplace of choice to accelerate the time to business value over the use of independent data asset providers or consumers.
- When seeking to monetize data products, look to marketplaces for the transactional infrastructure to allow internal efforts to focus on building unique and differentiated data products.
- Leverage providers that operate within or are optimized for your cloud providers of choice to reduce data movement complexity and improve integration consistency.
- Evaluate prospective data providers beyond their data product selection and coverage. Examples are integration/access (such as APIs), value-added capabilities and exception alerting.
- Adapt data management policies and standards to account for the realities presented by data marketplaces and exchanges.
- Explore the value of third-party data to increase analytic insights by either adding context as new attributes or through additional data science model features.

Gartner Recommended Reading

Smart Data Sharing Requires Mapping Use Cases to Architectures and Vendor Solutions

How to Monetize Data Assets With Your Data and Analytics Service Provider

Flip 'Don't Share Data' Mantras — Introducing Gartner's 'Must Share Data Unless' Data Sharing Model

Data Sharing Is a Business Necessity to Accelerate Digital Business

Top Trends in Data and Analytics for 2021: From Big to Small and Wide Data

Conversational Analytics

Analysis By: Rita Sallam

Benefit Rating: High

Market Penetration: 1% to 5% of target audience

Maturity: Adolescent

Definition:

Conversational analytics allows any user to ask voice or text questions of their data and receive back a natural language and, potentially, an AI-augmented visual analysis of the most statistically relevant and actionable insight for that user. Conversational analytics applies natural language processing as a means of interacting with a range of analytics technologies. They are often domain- and industry-specific due to specific ontologies and business knowledge required.

Why This Is Important

Expanding access to insights from analytics to all workers and even customers will be key to driving transformative business impact. However, access to analytics content from analytic and BI and data science platforms has mostly been limited to power users, business analysts and specialist data scientists with varying degrees of analytical and technical skill.

Business Impact

- Conversational analytics has the potential to expand adoption of analytics to more users and roles while reducing manual analysis. It is also being embedded in the applications and collaboration tools that every employee uses.
- For example, a sales manager might ask for a pipeline analysis. Based on his/her role and/or behavior, the system could show a narrative in text or voice of the most important insight and drivers along with visualizations showing key trends, patterns or outliers.

Drivers

- Wider availability of solutions. Today, conversational analytics capabilities are increasingly available from many analytics and BI platform vendors, from domain- and industry-specific platforms, or are built by service providers that integrate and customize the necessary components, ontologies and domain expertise.
- Mainstream capabilities require analyst skills today. Using a point-and-click paradigm to ask ad hoc questions and finding actionable insights from dashboards requires the advanced skill set of a power user or an analyst and manual exploration. Buyers are demanding easier-to-use tools to expand adoption and deliver insights to less skilled users.
- NLP capabilities have improved to support the types and complex questions for real-world use overcoming past user frustration with this technology.
- People are now using more collaboration tools, particularly with the expansion of remote work, and have experience with conversational capabilities with bots given their proliferation in other settings.

Obstacles

- Trust and adoption will depend on users being able to get answers to complex and domain-relevant questions. This requires a system that learns, and upfront effort to build domain-, industry- and organization-specific ontologies and data models.
- Most solutions are English only. This will limit global use.
- Although the natural language processing (NLP) is improving, users may still get frustrated with the system if they don't get the relevant answers they expect. Users are easily turned off even from one bad experience.
- Current systems are mostly question-and-answer. Truly conversational experiences are emerging and not yet mature.
- Conversational analytics represents the convergence of a number of technologies, including mobile, bots, AI, augmented analytics, and analytics and BI. It will mostly be an integration of technologies from multiple vendors in the near term until more out-of-the-box solutions are available.

User Recommendations

Data and analytics leaders looking to make analytics more pervasive should:

- Prototype current APIs 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, spoken language limitations, domain- and industry-specific ontologies, and types of analysis supported.

Sample Vendors

iGenius; Liquid Analytics; Marlabs; Oracle (Analytics Cloud); Qlik; Sisense; Stratifyd; Unscrambl

Gartner Recommended Reading

Magic Quadrant for Analytics and Business Intelligence Platforms

Critical Capabilities for Analytics and Business Intelligence Platforms

Tool: Visual Guide to Analytics and Business Intelligence Platform Capabilities

Top Trends in Data and Analytics for 2021

Multiexperience Will Be the New Normal for Consuming Analytics Content in the Augmented Era

At the Peak

Analytics Governance

Analysis By: Andrew White, Kurt Schlegel

Benefit Rating: High

Market Penetration: 1% to 5% of target audience

Maturity: Emerging

Definition:

Analytics governance is the enforcement of D&A governance policy along the analytics pipeline from data discovery through to analytics model deployment, and access to the analysis and insight. Though the markets use the term "governance" here, the reality is that what is being sought is not related to policy setting but actually executing and enforcing policy along the analytics pipeline. A more appropriate name would be analytics stewardship.

Why This Is Important

For many years, organizations have limped along with semitrusted data in their analytics pipeline. With the increased adoption of data lakes and data sharing in the last few years, the gap between expectations and reality is starting to hit home. With analytical and forecasting models breaking in 2020 due to the COVID-19 pandemic, business leaders are finally grasping the reality: they, their decisions and even their organizational survival is held hostage to bad data and analytics.

Business Impact

If organizations do not implement data and analytics governance through their analytics pipeline, no amount of spending on the latest analytics tool or technology will survive scrutiny. Worse, business decisions may backfire and organizational performance may suffer as a result. With the right business outcome and adaptive governance focus, the least amount of mission-critical data and analytics will be governed, thus assisting with trusted and reliable analysis and insight leverage.

Drivers

- 2021 is marked with small and wide data, not big data. It is also marked with data and analytics everywhere and at the edge. With these new trends, additional pressures are being put on your organization.

- A shift in focus from truth to trust in governing data and analytics assets due to the vastness of data now to hand for analysis and the lack of accountability in third party sources.
- Protection and provenance of the inbound data to the analytics pipeline and at-rest data in the warehouse or lake.
- Need for enhanced integrity of the analytical model being developed.
- Guidance for ethical consideration.
- Continually evolving permissions for access to the data for model development or for consumption of the analysis output even as organizational boundaries shift almost daily.
- Often third-party-driven retention requirements for risk mitigation.
- Preservation of privacy that may even conflict when operating across multiple jurisdictions.
- No amount of technology can help; though it is with technology that D&A governance policies are applied and enforced (stewardship) along your analytics pipeline.
- While the hype is firmly placed on analytics governance, the reality is that organizations need to focus on extending their D&A governance program along the data and analytics pipeline.

Obstacles

- The biggest obstacle is the lack of a clear line-of-sight between a piece of rogue or untrusted data in a data warehouse or dashboard and its impact on a business decision or outcome. This lack of visibility between data and outcome helps explain why business leaders seem disinterested in the work of governance and stewardship.
- The second is that many organizations think that “analytics governance” is actually something different and distinct to data and analytics governance. This is just natural forces looking at the boundaries in front, and not visionaries looking beyond to see the same patterns and solutions emerging.

User Recommendations

- Recognize the work of policy setting (i.e., governance); policy enforcement (i.e., stewardship) and policy execution (i.e., management). Apply your response to your analytic pipeline.
- Extend or connect your data and analytics governance work so that the policy setting and enforcement efforts can be aligned — this will reduce redundancy and save money, and lead to improved outcomes
- Note also that most cloud analytics and cloud infrastructure vendors really don't understand what your needs are in this market. They mostly think it all hinges on tracking data lineage. That is nice, but not sufficient.
- Don't assume your analytics, business intelligence, data science or artificial intelligence solutions support your requirements for analytics stewardship (or governance). At most, they might respect the odd rule and follow it (i.e., management/execution). You may need to build your own capability outside of those solutions, until the vendors wake up and build what you need.

Sample Vendors

Alation; Collibra; ZenOptics

Gartner Recommended Reading

Data and Analytics Leaders Must Use Adaptive Governance to Succeed in Digital Business

Use Enterprise Metadata Management to Extend Information Governance to Analytics

The State of Data and Analytics Governance Is Worse Than You Think

Data Literacy

Analysis By: Alan D. Duncan, Sally Parker, Donna Medeiros

Benefit Rating: High

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Definition:

Data literacy is the ability to read, write and communicate data in context, with an understanding of the data sources and constructs, analytical methods and techniques applied. It is the ability to describe the use-case application and resulting business value or outcome.

Why This Is Important

Data and analytics are pervasive in all aspects of all businesses, in communities and in our personal lives. The ability to understand, interpret and act upon data — data literacy — is increasingly foundational to the digital economy and society. Data literacy helps explain to the board how data and analytics manifest in a company's use cases, explain how to identify, access, integrate and manage internal and external datasets, and describe advanced analytics techniques and enabling AI.

Business Impact

Data-driven enterprises require explicit and persistent organizational change to achieve measurable business outcomes. Employees know their organization is serious about change only when they see their leaders changing their own behavior. CDOs need to promote and orchestrate "leadership moments" where they act as role models, exemplifying new cultural traits at critical points. Central to success will be the ability to guide the workforce by addressing both data literacy and data-driven culture.

Drivers

- With the steady rise of the digital economy, and the need for businesses to be digitally literate, there is growing recognition of the role that employees' data literacy plays within an organization's overall digital dexterity.
- The role of the data and analytics function has changed. It is now at the core of an organization's business model and digital platforms.
- CDOs can emulate their higher-performing peers by putting much more emphasis, energy and effort into meeting the change management requirements of their data and analytics strategies.
- Defining what data-driven behaviors are expected, using a "From/To/Because" approach, is central to employee development plans. It ensures that creators, consumers and intermediaries have the necessary data and analytics skills, knowledge and competencies.
- CDOs need to take immediate action to create and sustain data literacy. Quick wins build momentum, but lasting and meaningful change takes time because it requires people to learn new skills and behave in new ways.

Obstacles

- Lack of common data literacy models/frameworks/standards
- A piecemeal approach to training and certification
- Aversion to change
- Lack of talent and poor data literacy
- Lack of initiatives to address cultural and data literacy challenges within strategies and programs
- "Data literacy" means different things to different providers: from enhanced data visualization skills to fostering curiosity about data more broadly
- Overall adoption will still take years

User Recommendations

- Create a strong narrative vision of desired business outcomes, particularly with respect to innovation. Raise awareness through storytelling.
- Call out examples of “good” and “bad” data literacy to promote desired behaviors.
- Work with stakeholders who have enthusiasm and appetite, and who recognize that improved data literacy is a factor for success.
- Partner with HR and business leaders to identify the level of data literacy, learning goals and outcomes for various job roles and personas. Use data literacy assessments to evaluate current data literacy levels and desire to participate.
- Go beyond vendor product training to focus on people’s other role-related skills. Use a mix of training delivery methods (classroom, online, community, on the job) to improve overall learning effectiveness.
- Align training and self-service solutions with a broader data literacy portfolio to meet the data literacy needs of both data consumers and creators.

Sample Vendors

Avado; Coursera; Data To The People; Gartner Consulting; Pluralsight; Skillsoft; The Center of Applied Data Science (CADS); The Data Lodge; Udacity; Udemy

Gartner Recommended Reading

Roadmap for Data Literacy and Data-Driven Business Transformation: A Gartner Trend Insight Report

Tool: Communicating the Need for Data Literacy Improvement

Chief Data Officers Must Address Both ‘Skill’ and ‘Will’ to Deliver Data-Driven Business Change

Tool: Data Literacy Personas

Data Literacy Providers Will Accelerate the Time to Value for Data-Driven Enterprises

Decision Intelligence

Analysis By: Erick Brethenoux

Benefit Rating: Transformational

Market Penetration: 5% to 20% of target audience

Maturity: Emerging

Definition:

Decision intelligence (DI) is a practical discipline used to improve decision making by explicitly understanding and engineering how decisions are made and how outcomes are evaluated, managed and improved via feedback.

Why This Is Important

The current hype around automated decision making and augmented intelligence, fueled by AI techniques in decision making, is pushing DI toward the Peak of Inflated Expectations. The COVID-19 pandemic has revealed the brittleness of decision models; rebuilding those models to be resilient, adaptable and flexible will require the discipline brought by DI methods and techniques. A fast-emerging market around various software disciplines is starting to provide sensible answers for decision makers.

Business Impact

Decision intelligence helps organizations:

- Improve the impact of business processes by materially enhancing the sustainability of organizations' decision models based on the power of their relevance, the quality of their transparency and the strength of their resilience, thus making decisions more transparent and auditable.
- Reduce the unpredictability of decision outcomes by properly capturing and accounting for the uncertainty factors in the business context.

Drivers

- A dynamic and complex business environment, with an increasingly unpredictable and uncertain pace of business. The combination of AI techniques (such as NLP, knowledge graphs, machine learning), and the confluence of several technology clusters around composite AI, smart business process, decision management and advanced personalization platforms, are creating a new market around decision systems platforms supporting the DI discipline.
- Need to curtail unstructured, ad hoc decisions that are siloed and disjointed. Often uncoordinated, such decisions promote local optimizations at the expense of global efficiency.
- Expanding collaboration between humans and machines, supplemented by a lack of trust in technologies (such as AI) increasingly replacing tasks and promoting uneasiness from a human perspective. DI practices promote transparency, interpretability, fairness, reliability and accountability of decision models critical for the adoption of business-differentiating techniques.
- Tighter regulations that are making risk management more prevalent. From privacy and ethical guidelines to new laws and government mandates, it is becoming difficult for organizations to fully understand the risk impacts of their decisions. DI enables an explicit representation of decision models, reducing this risk.
- Uncertainty regarding decision consistency across the organization. Lack of explicit representation of decisions prevents proper harmonization of collective decision outcomes. This is remedied by DI.

Obstacles

- Decision-making silos have created data, competencies and technology clusters that are difficult to reconcile and could slow down the implementation of decision models.
- An inadequate organizational structure around advanced techniques, such as the lack of an AI center of excellence, could impair DI progress.
- Reputation-damaging outcomes from autonomous decision models (from embedded analytical assets to self-contained machine agents) and the failure to understand their collective impact impede DI adoption.
- Lack of proper coordination between business units and inability to impartially reconsider critical decision flows within and across departments diminish the effectiveness of early DI efforts.

User Recommendations

- Improve the outcomes of decision models and accommodate uncertainty factors by evaluating the contributing decision-modeling techniques.
- Promote the sustainability of cross-organizational decisions by building models using principles aimed at enhancing traceability, replicability, pertinence and trustworthiness.
- Improve the predictability and alignment of decision agents, by simulating their collective behavior while also estimating their global contribution versus local optimization.
- Develop staff expertise in traditional and emerging decision augmentation and decision automation techniques, including descriptive, diagnostic (interactive data exploration tools), predictive (machine learning) and prescriptive (optimization, business rule processing and simulation) analytics.
- Tailor the choice of decision-making technique to the particular requirements of each decision situation by collaborating with subject matter experts, AI experts and business process analysts.

Gartner Recommended Reading

Improve Decision Making Using Decision Intelligence Models

How to Manage the Risks of Decision Automation

How to Choose Your Best-Fit Decision Management Suite Vendor

AI Security: How to Make AI Trustworthy

Top Strategic Technology Trends for 2021: AI Engineering

Continuous Intelligence

Analysis By: Pieter den Hamer, W. Roy Schulte

Benefit Rating: Transformational

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Definition:

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

Why This Is Important

CI plays a major role in digital business transformation and optimization projects. A key benefit is improved situational awareness and a common operating picture across business functions by providing real-time dashboards, alerts and next-best-action recommendations. 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.

Business Impact

The current hype is focused on holistic, integrated CI solutions that share real-time information from myriad sources with various departments and applications to support multiple business functions. This is a further evolution of many existing but more local CI point solutions for specific applications. Examples of more integral CI include real-time 360-degree views of customers, supply chain networks and enterprise nervous systems in airlines, railroads and other transportation operations.

Drivers

- CI systems leverage real-time and contextual data to support, augment or automate decisions for customer interaction, manufacturing, fraud detection, supply chain management or other areas. CI is also used for real-time (re)scheduling and optimization, for example, to allocate resources in the most efficient manner possible.
- CI goes beyond real-time descriptive, diagnostic and predictive analytics by supplying prescriptive information about the best available action in the current context. 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.
- The hardware and software technologies for holistic, integrated CI are available and affordable. These include inexpensive sensors, publish-and-subscribe messaging systems, such as Apache Kafka, event stream processing platforms and augmented analytics. CI may also leverage decision management tools, machine learning, intelligent business process management suites (iBPMS), IoT platforms or other development, middleware and analytics products.
- The growing complexity, and the desired scalability, speed and automation of decision making fuel the adoption of decision intelligence. This discipline includes the explicit modeling of decisions as a foundation to understand, assess and, where needed, reengineer decisions. It also encompassess the combination of connected insights, contextual analytics and CI.
- With increasing dynamics and disruptions in business, companies need to be more adaptive and resilient. CI enables constant monitoring for threats and opportunities, including suggested or automated responses to those events. To further improve this, adaptive machine learning combined with CI paves the way for what ultimately may become autonomous and constantly adapting, and self-learning processes and organizations.

Obstacles

- CI can be very challenging in terms of the full integration of real-time analytics with business processes and their supporting applications, which, as a result, need to be redesigned. This requires close collaboration between disciplines such as data and analytics, IT application teams and business process designers.
- Holistic, integral CI is applied at a cross-functional enterprise or an ecosystem level, resulting in a more complete situational awareness and more optimal decisions. However, to achieve this, resistance to change and a silo-oriented culture need to be overcome.
- Many companies lack the skills necessary to develop custom-built solutions for CI. These skills include streaming data processing and time-series data analysis, which are significantly different from processing and analyzing data “at rest.”
- Real-time integration of multiple data sources leaves little room for dealing with semantic differences or data quality issues, implying the need for mature data management practices.

User Recommendations

- Involve and work with business managers and subject-matter experts as early as possible in the requirements-gathering and implementation processes, because when CI is implemented, it fundamentally affects the design of business processes.
- Subscribe to SaaS offerings or acquire packaged applications or devices that provide internal continuous intelligence as a point solution, to reduce the effort of achieving CI. However, more integral, cross-functional CI will still entail custom design and integration with multiple applications. This will require multidisciplinary collaboration among business domain experts, change managers, architects and developers.
- Hire outside service providers or train your staff on the new disciplines if your enterprise wants to build its own solutions and does not already have staff expertise in messaging, stream analytics, machine learning and decision management disciplines.

Sample Vendors

Datapred; IBM; Iguazio; Quantexa; Radicalbit; SAS; Swim; TIBCO Software; Transvoyant; Ublique

Gartner Recommended Reading

Presentation: The Future of Data and Analytics: Reengineering the Decision, 2025

Innovation Insight for Continuous Intelligence

Three Ways to Derive Information From Event Streams

How to Use Real-Time Analytics When Building an Enterprise Nervous System

Data & Analytics for Good

Analysis By: Carlie Idoine, Jorgen Heizenberg

Benefit Rating: Moderate

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Definition:

“Data & Analytics for Good” is a movement in which people and organizations transcend organizational boundaries to use data and data-driven insights for social impact. The usage may be within a data sharing, analytics and BI context or in more sophisticated data science and machine learning use cases and specifically does not include leveraging social causes to market products or services.

Why This Is Important

NGOs and public-sector organizations try to be more data-driven, but lack knowledge, skills, expertise and access to tools to leverage data to fulfill their missions. Meanwhile, commercial organizations (vendors and end-user organizations) have D&A expertise that can be used for the good of society. By crossing traditional organizational boundaries, these stakeholders unite in their efforts to leverage data for good and to provide more meaningful work to the most sought-after employees.

Business Impact

The "Data & Analytics for Good" movement gives resources to the public sector and NGOs through free or reduced-cost technology, data and people. In the commercial sector, participation in "D&A for Good" initiatives can be through philanthropic benefits that attract and retain workers, and provide resources. "D&A for Good" initiatives can signal social responsibility to investors. From a technology and vendor perspective, they can drive a positive impact on both marketing and sales.

Drivers

Focus on "Data & Analytics for Good" initiatives is growing with increased visibility and understanding of the value provided from these efforts.

- "Data & Analytics for Good" efforts initially focused on educational enhancement, providing clean water, reliable food, ecological management and arts and science community support.
- The number of organizations — from universities and communities to vendors — having a focus on "Data & Analytics for Good" has increased.
- D&A has the transformative power and availability to gain insights into the descriptive existence and diagnostics of the root causes of human suffering, and predict and prescribe how to action changes which will mitigate it.
- Significant market momentum for "Data & Analytics for Good" comes from vendors (both software and services), and has been especially evident in relation to COVID-19 response efforts.
- Many organizations' COVID-19 responses have spotlighted exceptional "D&A for Good" initiatives as organizations teamed together to share data and analytic resources to combat and manage the crisis.

Obstacles

- Justification for “Data & Analytics for Good” is difficult to initiate and maintain because the goals and objectives are considered altruistic, and lose influence relative to business delivery-driven efforts.
- “D&A for Good” programs are often dismissed because the funding stream is considered temporary or at least inconsistent.
- Some “D&A for Good” programs are rejected when they seek to qualify inclusion or delivery based upon personally identifiable information or data that is considered ethically dangerous.
- Lack of transparency can lead to negative unintended consequences; data ethics and trust must be incorporated to avoid data misuse.
- Low levels of data literacy get in the way of effectively using the contributed data and analytics to achieve the desired social impact.
- Legal impediments, technical data format standards and the practical issue of data cataloging and aggregation have also hindered efforts.

User Recommendations

- Leverage free resources (people/services, software, technology, data) from organizations that support “D&A for Good” projects.
- Participate in community events such as those hosted by DataKind, Kaggle and universities to collaborate on “D&A for Good.” Contribute to, and explore, open data in support.
- Allow employees time to work on philanthropic initiatives as part of social responsibility. Use this HR benefit as a differentiator in recruiting and skills’ enhancement.
- Evaluate internal, external and open data to assess its usefulness for social purpose, while also adhering to privacy and security policies. Instill data ethics considerations in data use and sharing.
- Drive data literacy to help identify, understand and recommend controls for “D&A for Good” use cases in an effort to provide transparency without endangering individuals’ privacy or sensitivities.
- Grow awareness about “D&A for Good.” Share internal and external case studies as well as resources that demonstrate what “D&A for Good” is and its potential impact.

Sample Vendors

Alteryx; DataKind; DataRobot; Esri; Google; IBM; Salesforce; SAS; Tableau; Teradata

Gartner Recommended Reading

How to Use Data for Good to Impact Society

Modernize Your MDM Program With External Master Data Sharing

Dare to Dream! Give Your Data and Analytics Initiatives a Purposeful Mission to Improve the World

Magic Quadrant for Data and Analytics Service Providers

Smart Data Sharing — Five Insights to Get It Right

Edge Analytics

Analysis By: Eric Hunter, Ted Friedman

Benefit Rating: High

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Definition:

Analytics is the discipline that applies logic (e.g., “rules”) and mathematics (“algorithms”) to data to provide insights that drive organization strategy and executive decision making. “Edge” analytics means that the analytics are executed in distributed devices, servers or gateways located outside of data centers and public cloud infrastructure closer to where the data and decisions of interest are created and executed.

Why This Is Important

Gartner client inquiries related to the data and analytics (D&A) implications of edge increased by nearly 35% year over year in 2020 (and by nearly 400% since 2018). With a growing relevance, by 2023, over 50% of the primary responsibility of D&A leaders will comprise data created, managed and analyzed in edge environments. Demands for real-time decision making closer to where the data and decisions of interest are created and executed are one of many drivers for edge analytics.

Business Impact

The origins of edge analytics offerings were primarily in the support of decentralized deployments for device-isolated insights. However, connectivity advances, demands for cross-device analytics and innovations surrounding IoT have dramatically increased the scale and complexity of edge analytics use cases. Real-time event analytics and decision making, autonomous behavior of assets and fault-tolerant applications hold tremendous potential value for enterprises in many industries.

Drivers

- Advantages of edge analytics include faster response times, reduced network bottlenecks, data filtering, reliability, increased access to data and reduced communications costs.
- The increase of distributed cloud and hyperconverged solutions from public cloud providers including Amazon Web Services (AWS Outposts), Microsoft (Azure Stack/Arc), Google (Anthos) are further decentralizing previously cloud-restricted workloads. This perimeter expansion of the cloud brings compute and storage closer to the edge — creating new possibilities for edge-centric analytic workloads.
- 5G networks continue to grow in relevancy and, combined with mobile edge computing, will increase edge analytics use cases — particularly for latency-sensitive deployments.
- By distributing analytics capabilities to edge environments, data-centric solutions can enable more real-time value. For scenarios that require very low latency, the ability to capture and analyze data close to the place/time of origin reduces latency issues.
- More analytics solutions, such as those supporting IoT use cases, need to operate in disconnected (or intermittently connected) scenarios. By bringing more powerful analytics capabilities to edge environments, these solutions need not rely on centralized data centers or cloud resources.
- By provisioning advanced analytics and AI capabilities to edge environments, the assets driven by those environments can behave in an autonomous manner with no support from external data sources or processing capabilities. As demand grows for “smarter” physical assets in many industries, supporting autonomous behavior will be a common requirement.
- Governance issues related to sensitive/regulated data can constrain D&A teams from adopting centralized/cloud-based environments — moving data outside its originating geography can violate sovereignty regulations. By locating analytics in edge environments, the data remains in the originating locations, increasing the likelihood of compliance.

Obstacles

- Some of the disadvantages of edge analytics include increased complexity, reduced data granularity, lack of cross-device analytics, overhead of device maintenance and technical currency demands.
- Architectural design and development best practices for traditional or cloud-resident analytics do not carry over directly for edge analytics use cases.
- This fragmented market includes two extremes in terms of provider scale — with early and unknown startups competing head to head with global mega vendors — driving a mix of platform/protocol standards and complicating going concern considerations for prospective buyers.
- Enterprise standards and governance (data privacy, security, etc.) can complicate edge analytics initiatives and delay overall value realization objectives.
- From physical endpoints to platforms spanning data collection/integration and analysis — the capabilities of edge analytics product and service offerings are diverse, increasing the provider evaluation demands.

User Recommendations

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

- Provide analytic insights for individual devices, assets or a larger distributed site even in the midst of disconnection from cloud or data center infrastructure and resources (e.g., driverless cars).
- Provide data sovereignty. Many regulations or data privacy laws require data be kept in the location of origin or the organization deems the transfer of data to introduce too many security vulnerabilities.
- Understand that network connectivity does not have the ability to support desired latency or stability requirements.
- Understand that cross-device interdependencies serving as part of a larger system require edge-resident analytics.
- Understand that it would cost too much to upload the full volume or fidelity of generated data and that there is no benefit to moving device-level data to a central location for aggregated analysis.

Sample Vendors

Amazon Web Services; Arundo; CloudPlugs; FogHorn; Microsoft; Samsara; ThingWorx; TIBCO Software

Gartner Recommended Reading

Top Trends in Data and Analytics for 2021: Data and Analytics at the Edge

2021 Strategic Roadmap for Edge Computing

Predicts 2021: Cloud and Edge Infrastructure

Tech Providers 2025: The Future of Edge

Emerging Technologies: Edge AI Adoption Patterns Deliver Business Value

Natural Language Generation

Analysis By: Bern Elliot

Benefit Rating: High

Market Penetration: 1% to 5% of target audience

Maturity: Emerging

Definition:

Natural language generation (NLG) solutions automatically convert structured data and, in some cases, unstructured data — such as that found in a database, an application or a live feed, or images — into a text-based narrative. This makes the data easier for users to access by reading or listening, and therefore to comprehend.

Why This Is Important

NLG solutions can improve operational efficiency, making it easier to appraise, via summary, large or complex material and data, enabling new options for business process automation. Most solutions currently in the market are based on an older “slot-filling” methodology. But emerging solutions are evaluating how to leverage transformer artificial intelligence (AI) techniques to generate natural novel narratives, as well as other AI techniques to enable more complex use cases and increased automation.

Business Impact

NLG supports a number of productivity-enhancing use cases that can reduce the need for writers. It can clarify complex information such as analytic reports, can increase the speed at which textual information can be produced and shared, and can allow applications to communicate with users and audiences in a more fluid and natural manner. The emerging translator solutions hold the promise of expanding the scope and quality of what can be generated, and the breadth and complexity of the use cases that could be supported.

Drivers

The most common uses cases for NLG driving adoption fall into several categories:

- **Enhance understanding of business analytics.** For instance, integrating NLG functionality with existing analytics and business intelligence (BI) and data science initiatives.
- **Article-type short summaries.** For instance, writing summaries or analysis of business data, financial data, wealth management information, or sports.
- **Conversation responses.** For instance, writing personalized communications to customers via email or text.
- **Easing data access.** For instance, writing short, prose-base product descriptions based on database product information. These might then be posted as a reply to website information requests.
- **Generating variants of outbound messaging and marketing copy.** The last four years have seen growth in the number of short-form NLG specialist vendors.

Emerging, more complex, use cases include:

- The combination of NLG with automated pattern/insight detection and self-service data preparation. This can drive the user experience of next-generation augmented analytics platforms. Users have varying degrees of analytics skill to correctly interpret and act on statistically significant relationships in visualization. This use case could also expand the benefits of advanced analytics to a wider audience of business users, as well as making existing analysts and data scientists more efficient.

- 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 natural language query (NLQ), chatbots and NLG via virtual personal assistants.
- Conversational solutions, including virtual assistants, will be able to use NLG methods to enable more complex and natural-sounding interactions.

Obstacles

NLG solutions based on slot-filling are mature. However, major barriers exist for more sophisticated solutions that leverage advanced AI techniques:

- **Complexity barrier.** Advanced AI techniques, such as transformer-based language generation and case-based learning, are complex applications to build. The optimal algorithms and parameter settings must be explored. Often, these have significant compute and memory requirements, which add to cost and challenges.
- **Cost to scale.** Additionally, scaling these applications for production may require optimization and possibly specialized hardware to contain costs.
- **Advanced application development tools.** In order to properly leverage the newer AI techniques, NLG solutions will need to offer tools that enable users to customize the solution to their specific domains and use cases. As a result, much more-advanced and, critically, more user-friendly, tools will be needed.

User Recommendations

- **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 organizations** that are wishing to have their analytics, BI solutions and other classes of visual information accessible to those audiences that are visually impaired; for instance, to comply with the Americans with Disabilities Act (in the U.S.) and similar mandates in other countries.

Sample Vendors

ARRIA NLG; Automated Insights; AX Semantics; Marlabs; Narrative Science; Salesforce; Sasa Software; ThoughtSpot; Yseop

Gartner Recommended Reading

2021 Strategic Roadmap for Enterprise AI: Natural Language Architecture

Magic Quadrant for Analytics and Business Intelligence Platforms

Data Storytelling

Analysis By: James Richardson

Benefit Rating: High

Market Penetration: 5% to 20% of target audience

Maturity: Early mainstream

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.

Why This Is Important

Too many decision makers still overlook 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.

Business Impact

The business impact of data delivered as a story can be much higher than dashboards and reports, as a story form is familiar to all people. From an ROI perspective, data storytelling can help drive adoption of A&BI platforms, by repositioning them from simply visualizing data to becoming the key medium for effective communication of insights about data. This is important when Gartner research shows that adoption of A&BI platforms is still less than what it should be, to be of most impact.

Drivers

- It's now recognized that KPI-centered dashboards are no longer the sole or most effective way of delivering data. A data storytelling approach can transform how analytics and data science teams work by getting them to focus on how their audience, often nontechnical decision makers, needs data to be presented to them to be most compelling.
- The functional capabilities to create data stories are now widely available. Most A&BI platforms now include a basic functionality to create and share data stories. These stories can take several forms — most frequently data-connected slideshows or storyboards, 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.
- Machine-generated data storytelling (via applied machine learning [ML]) is fast emerging, offering the promise of news-style headlines and narratives generated automatically and specifically for individuals. This is almost an inevitability as there aren't enough human analysts for the analyzable data available; ML is better at spotting patterns than most humans and automation is economically viable.

Obstacles

- The use of data storytelling draws on an emergent set of skills, practices and behaviors around how data is socialized and used in organizations. Many organizations do not have these skills in place.
- Data storytelling is a part of a broader movement oriented around data literacy, and explaining and expressing data and analytics in a business-friendly and relevant way. A low level of data literacy is an inhibitor to the use of these techniques.
- Machine-generated data stories may not gain traction if they are not relevant, understandable or explainable to the intended recipients.

User Recommendations

- Evaluate and experiment with the data storytelling capabilities of A&BI platforms. Examine how their incumbent portfolio of technologies supports the creation of storyboard-style presentations with embedded analytical content.
- Task members of their analytics team with investigating data storytelling as an extension to their use of interactive visual exploration and analytic dashboarding. This will provide a richer delivery of information by adding narrative and context.
- Prepare programs to develop and instill the 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.

Sample Vendors

Domo; Narrative Science; Outlier; Qlik; Tableau; Toucan Toco; Yellowfin

Gartner Recommended Reading

Beyond BI Reporting: Engaging Decision Makers Through Data Storytelling

How to Get More Value From Data Visualization

Augmented Analytics: Teaching Machines to Tell Data Stories to Humans

Explainable AI

Analysis By: Farhan Choudhary, Sumit Agarwal

Benefit Rating: High

Market Penetration: 1% to 5% of target audience

Maturity: Emerging

Definition:

AI researchers define “explainable AI” as an ensemble of methods that make AI algorithms’ outputs sufficiently interpretable. Gartner defines Explainable AI as a set of capabilities that describes a model, highlights its strengths and weaknesses, predicts its likely behavior, and identifies any potential biases. It can clarify a model’s functioning to a specific audience to enable accuracy, fairness, accountability, stability and transparency in algorithmic decision making.

Why This Is Important

Explainable AI (XAI) gives the visibility into how a model arrived at a particular decision. This helps in building trust, confidence and understanding in AI systems. In highly regulated sectors such as insurance or banking, regulations directly or indirectly mandate the need for model explainability in order to properly manage model risk.

Business Impact

Explainable AI is the responsibility of both vendors (data scientists and solution developers) and also for end-user organizations that consume them. Not supporting this capability puts businesses and decision making at risk. However, it is to be noted that different levels of explainability are required for customers, the organization’s management and employees, society and regulators to direct AI governance.

Drivers

- Risks imposed by AI solutions that are not well understood cannot be mitigated. The lack of model "understandability" among model users, managers and consumers impacted by models' decisions severely limits an organization's ability to manage AI risk. Whether organizations like it or not, they are seen as responsible by the consumers they serve, with around half of the U.S. and U.K. consumers who responded to a Gartner survey saying that "your organization should be accountable when AI goes wrong."

- Not ensuring explainability invites model risk that can lead to financial loss, poor business and strategic decision making, or damage to organizational reputation.

- With a lot of organizations shifting to augmented decision-making capabilities with the use of AI models, they should be able to explain how an AI model arrived at a particular prediction/decision.

- Explainable AI capabilities are prebuilt into platforms and the innovations in the open source community to explain and interpret models are on the rise.

- There are ethical and moral considerations that need to be accounted for while relying on augmented decision making, often supported by thorough governance and auditing capabilities for these models.

- Some AI models tend to use personally identifiable information (PII)/protected health information (PHI) data, which, if not handled responsibly can lead to ethical and privacy concerns. Ensuring explainability on how the data was fetched, what features it has, was it anonymized and so forth, protects organizations from potential lawsuits.

- There are new regulations and legal interventions taking place which mandate the use of explainable AI methodologies.

- Explainable models also help with attrition, so data scientists who quit the job do not leave black boxes behind them.

Obstacles

- Explainable AIs are often looked at as a task or a step required while creating AI projects toward the end of the AI life cycle, but they have to be continuous and tested throughout training, development and production phases.
- There's an inherent lack of trust in AI systems which keeps organizations from adoption since they're simply not aware of explainable AI techniques or frameworks.
- Explainability tools are fragmented and XAI is often consumed in an oversimplification such as showing feature importance to end users. While that approach works in the beginning, explainable AI is much wider than that and requires heavy intuition and understanding of the subject.
- Organizations that focus on the accuracy of the models rather than on the interpretability stall their decisions on creating a more explainable AI.
- Explainability is often confused with ML interpretability. While the latter serves data scientists, the former applies to different personas interacting with the AI life cycle.

User Recommendations

- Define a range of actions that can be taken independently, that identify unacceptable results, and that flag those results for human intervention. Minimizing the number of incorrect results derived from AI is critical, as users will lose trust in a poorly performing system.
- Educate, train and foster ongoing conversations with key stakeholders, including line of business managers, legal and compliance, to understand the AI model's explainability requirements, challenges and opportunities.
- Strive for explainable AI for each model along the dimensions of business, data, algorithms, models and production.
- Accept deficiencies in explainability as a natural consequence of systems becoming increasingly complex. Document notable deficiencies or potential biases, so that they can be used to make corrections in the future.
- Establish the role of AI model validator, a data scientist whose job is to ensure that models are explainable, robust and meet all possible constraints.

Sample Vendors

Dataiku; DreamQuark; Fiddler; Google; H2O.ai; IBM; Microsoft; Modzy; Superwise.ai; TruEra

Gartner Recommended Reading

Top 5 Priorities for Managing AI Risk Within Gartner's MOST Framework

AI Security: How to Make AI Trustworthy

5 Myths About Explainable AI

Build Trust in AI Through Explainability

Prescriptive Analytics

Analysis By: Carlie Idoine, Peter Krensky

Benefit Rating: High

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Definition:

Prescriptive analytics is 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.

Why This Is Important

Prescriptive analytics provides capabilities to further automate/augment decision making to improve business responsiveness and more optimal outcomes. From a "purist" perspective, the term "prescriptive analytics" is a broad category with little hype, encompassing components with varying positions across the Hype Cycle and various levels of maturity. Such components include optimization, rules combined with predictive techniques and decision intelligence.

Business Impact

Prescriptive techniques support:

- Strategic, tactical and operational decisions to reduce risk, maximize profits, minimize costs, or more efficiently allocate scarce or competing resources.
- Recommendations for a course of action that best manages the trade-offs among conflicting constraints and goals.
- Exploration of multiple scenarios and comparison of recommended courses of action.
- Strategic and tactical time horizons as well as real-time or near-real-time decision making.

Drivers

- Maturing and expanding data science initiatives, better algorithms, more cost-effective cloud-based computing power and a substantial increase in available data.
- With improvement in analytics solutions, data quality, skills and broader use of predictive analytics, prescriptive analytics will continue to advance.
- In addition, the increasing popularity of graph techniques provides a great substrate for prescriptive analytics techniques, highlighting early signals for actions, causality links and forward paths of actions, facilitating the implementations of decisions and actions.
- The post COVID-19 reset with a focus on optimization and other advanced techniques with an emphasis on prioritizing actionable, proactive insight — as opposed to the more traditional reactive reporting.
- AI platforms and decision management tools increasingly include prescriptive techniques, driving user acceptance and potential value to the organization.
- Prescriptive analytics ranges from relatively straightforward rule processing to complex simulation and optimization systems.
- Prescriptive analytics continues to evolve, responding to ever greater complexity in business, with more need for more advanced prescriptive analytics and composite AI, e.g., combining rules/decision management with machine learning or optimization techniques.
- Organizations continue to improve and optimize their decision making, by applying decision intelligence and decision modeling to support, augment or automate decisions more effectively. Prescriptive analytics is a key enabler of this approach.

Obstacles

- Lack of expertise for how and where to apply prescriptive techniques.
- Lack of formal operationalization methods and best practices.
- Historic requirement for separate advanced analytics software that specializes in prescriptive techniques with little cohesion across the analytic capability continuum from descriptive to diagnostic to predictive to prescriptive.
- Even established use cases can fall victim to common data science challenges such as data quality, bias and talent shortages.
- Although it is a necessary competence, prescriptive analytics does not automatically result in better decision making.

User Recommendations

- Start with a business problem or decision where there are complicated trade-offs to be made, multiple considerations and multiple objectives.
- 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.
- Look for packaged applications that provide specific vertical or functional solutions, and service providers with the necessary 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.

Sample Vendors

AIMMS; Decision Lens; FICO; Frontline Systems; Gurobi; IBM; River Logic; SAS; Sparkling Logic; Veriluma

Gartner Recommended Reading

When and How to Combine Predictive and Prescriptive Techniques to Solve Business Problems

Predicts 2021: Analytics, BI and Data Science Solutions — Pervasive, Democratized and Composable

Worlds Collide as Augmented Analytics Draws Analytics, BI and Data Science Together

Effective Use of Supply Chain Analytics to Mitigate Business Disruptions

Sliding into the Trough

Citizen Data Science

Analysis By: Carlie Idoine, Shubhangi Vashisth, Rita Sallam

Benefit Rating: Transformational

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Definition:

Citizen data science is a set of capabilities and practices that allow users to extract advanced analytic insights from data without the need for extensive data science expertise. This provides responsive insights and faster time to insight for driving business decisions.

Why This Is Important

Innovations in augmented analytics tools enable those without expert data science knowledge and experience to be productive in applying data science and machine learning (DSML) methods within their analyses. Citizen data science helps unlock new insights beyond use of basic descriptive and diagnostic capabilities, enabling democratization of analytics capabilities as well as an upskilling path and new opportunities for business analysts and developers.

Business Impact

Citizen data science forms the foundation of next-generation analytics and can be leveraged to:

- Make insights from DSML more accessible and pervasive.
- Narrow the DSML talent gap due to the shortage and high cost of data scientists.
- Bring extensive domain expertise and increase efficiency of expert data scientists.
- Perform specific phases of the analytics life cycle (such as feature generation and selection, and algorithm selection) to scale and focus use of expertise where needed.

Drivers

- Historically, building DSML models required expert data scientists who are difficult and expensive to hire and retain. Citizen data science helps overcome such limitations.
- Central to citizen data science is the availability of augmented analytics capabilities. These include automated, streamlined data access and data engineering; augmented user insight through automated data visualization and exploration; modeling and pattern detection including feature engineering, model selection and validation; automated deployment and operationalization; and capabilities to support collaboration and sharing.
- Citizen data science will be a key driver of analytics adoption for the foreseeable future. Many business users want to upskill their analytics knowledge and expertise and may already be doing so. This population has become so prevalent that tools and features have been designed specifically for their use.

Obstacles

- Upskilling in advanced DSML techniques and approaches is important to derive value from citizen data science. Classroom learning provides a foundation but must be supported by on-the-job learning and experimentation.
- Tools with augmented analytics capabilities and additional processes to manage creation and sharing of models will be required to support citizen data science.
- There is still a need to (statistically) validate results of citizen data science by expert data scientists.
- Expert data scientists often resist or underestimate the effectiveness of citizen data science approaches.
- Citizen data science is often deemed to be just a preliminary, elementary step and not a fully functional DSML approach.
- Citizen data science leveraged in silos with no oversight or collaboration among experts and others with a vested interest in DSML success could lead to duplication of data engineering and analytic effort, lack of operationalization and limited visibility and standards.

User Recommendations

- Scan opportunities for citizen data science to complement existing analytics and expert data science initiatives across the data science life cycle.

- Define the citizen data scientist as a formal persona. Define its “fit” relative to other roles, and identify those who fit the citizen data scientist profile.
- Track the capabilities (technology) and roadmaps of existing business intelligence (BI) and data science platforms and emerging startups for support of augmented features.
- Educate business leaders and decision makers about the potential impact of a broader range of users leveraging DSML to gain leadership support.
- Acknowledge that you still need specialist data scientists to validate and operationalize models, findings and applications.
- Provision augmented analytics tools (including but not limited to citizen data science tools), platforms and processes to support and encourage collaboration between business users, application developers and data science teams.

Sample Vendors

Aible; Alteryx; BigSquid AI; Dataiku; DataRobot; dotData; H2O.ai; SAS; SparkBeyond; Tellius

Gartner Recommended Reading

Worlds Collide as Augmented Analytics Draws Analytics, BI and Data Science Together

Build a Comprehensive Ecosystem for Citizen Data Scientists to Drive Impactful Analytics

Pursue Citizen Data Science to Expand Analytics Use Cases

The 5 Myths of Citizen Data Science

Best Practices to Avoid Citizen Data Science Failure

Graph Analytics

Analysis By: Mark Beyer, Rita Sallam, Jim Hare, Afraz Jaffri

Benefit Rating: High

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Definition:

Graph analytics 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. Graph analytics is typically portrayed via multicontext visualization for business user consumption.

Why This Is Important

- Graph analytics has proven value in specific use cases (disease tracking, supply tracing, crime prevention, anti-fraud, and more).
- Graph technology is now ready to expand into broader use cases that require path analysis, network coordination (of humans or machines), macro effects on direct market or services delivery, and microeffects on broader environments.
- The utilization of graph analytics is necessary in order to develop knowledge graphs, which are also accelerating in terms of market adoption.

Business Impact

Graph analytics:

- Analyzes underleveraged data for insights in complex connected data
- Is highly effective at assessing risk and responding to it to analyze fraud, route optimization, clustering, outlier detection, Markov chains, and more
- Identifies issues within an organization regarding liability and suggests proactive resolution
- Identifies peculiarly successful patterns in an organization
- Extends data discovery capabilities in modern business intelligence and analytics platforms

Drivers

Graph analysis is showing increased demand across all global regions, but not across all industry verticals:

- Graph analytics generally exhibits demand in 10% to 15% of the market.

- The COVID-19 pandemic has increased graph analytics over 90% in healthcare management, clinical research and healthcare supply chain use cases.
- Use cases that require analysis across highly complex models are developed and used within machine learning with the output stored in graph databases.
- Graph databases are ideal for storing, manipulating and analyzing the widely varied perspectives in the graph model due to their graph-specific processing languages, capabilities and computational power.
- Established AI techniques (such as Bayesian networks) are increasing the power of knowledge graphs and the usefulness of graph analytics through further nuance in representational power.
- Graph analytics also offer capabilities relative to contact tracing applications — showing significant advancement during the ongoing pandemic.

When graph analytics is used across data and metadata, metadata from unexpected sources adds to the graph analysis capabilities in the following ways:

- Certain combinatorial evaluations can build data “push” models that recommend new data assets to existing use cases by analyzing data access logs and analytical model development.
- Machine-enabled data profiling combined with graphs can evaluate brand new assets for similarities as compared to more familiar datasets — identifying certain characteristics of new data that are already aligned to AI techniques or ML features.
- Determines whether new and unfamiliar data is similar to training datasets already in use.

Specific industries are exhibiting adoption for vertical market requirements, and other use cases that span many industry verticals in a horizontal fashion are seeing early to moderate levels of adoption, such as:

- Law enforcement, epidemiology, genome research, anti-money laundering.
- Route optimization, market basket analysis, fraud detection, social network analysis or location intelligence.

Obstacles

- Graph analytics and the closely related graph databases are driving a demand for new skills related to graph-specific knowledge, which may limit growth in adoption. Some vendors have created graph analytic solutions that make it possible to execute graph analytics using SQL.
- New skills required include knowledge and experience with the Resource Description Framework (RDF), property graphs, SPARQL Protocol and RDF Query Language (SPARQL), as well as executing graph analysis in Python and R.

User Recommendations

- Test graph analytics to address use cases that exhibit development, coding and data models that are overly complex using traditional SQL-based queries and visualizations.
- Consider graph analytics to enhance pattern analysis — especially in the verticals and use cases noted above.
- Transition metadata analytics from simple catalog search and discovery into a graph analysis model to identify user communities that conduct statistical and logical processes that are applied to shared datasets.
- Implement interactive user interfaces with the graph elements to find insights and analytic results, and store the outputs/results for repeated use in a graph database.
- Train existing personnel how to align data assets, statistical processes, algorithms to create training datasets and building identification processes to detect data changes that will drive changes in the analytical models.

Sample Vendors

Cambridge Semantics; Digital Reasoning; Elastic; Maana; Siren; SynerScope

Gartner Recommended Reading

Graph Technology Applications and Use Cases

Connecting the Dots: Why Graph Analytics Are Key to Understanding Human and Machine Misbehavior

How to Build Knowledge Graphs That Enable AI-Driven Enterprise Applications

Augmented Analytics

Analysis By: Rita Sallam

Benefit Rating: Transformational

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Definition:

Augmented analytics uses AI and ML techniques 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.

Why This Is Important

Many of the activities associated with preparing data, finding patterns in data, building models on complex combinations of data, and sharing insights with others, remain highly manual. This limits user adoption and potential business impact.

Business Impact

- Augmented analytics is transforming how and where users interact with analytics content as it has become a core component of most analytics and BI and data science platforms.
- Insights from advanced analytics — once available only to skilled analysts, citizen data scientists and data science specialists — are now in the hands of business analysts and a broad range of decision makers and operational workers across the enterprise — the augmented consumer — driving new sources of business value.

Drivers

- Organizations increasingly want to analyze more complex datasets combining diverse data from across the enterprise as well as from external sources. With an increasing number of variables to explore in data harmonized from many diverse datasets, it is practically impossible for users to explore every possible pattern combination, and even more difficult to determine whether their findings are the most relevant, significant and actionable. Expanding use of augmented analytics will reduce the time users spend on exploring data, while giving them more time to act on the most relevant insights.
- Augmented analytics capabilities are increasingly mainstream features of data preparation, analytics and BI platforms and data science and machine learning tools. They are also being embedded in enterprise applications and domain and industry specific solutions. This is delivering insights most relevant to a broad set of application users to improve decision-making and actions.
- Dynamic data stories are an example of a combination of augmented analytics features used to automate insights. This combines augmented analytics with natural language query (NLQ), natural language generation (NLG) and anomaly detection into dynamically generated data stories delivered to users in their context. This type of user experience will reduce the use of predefined dashboards for monitoring and analysis and increase the use of augmented analytics.

Obstacles

- Trust in autogenerated models. Organizations must ensure that the augmented approach is transparent and auditable for accuracy and bias, and that there is a process to review and certify analyses created.
- Training. With more automation comes greater user responsibility and the need for more, but different user training.
- Collaboration. Establishing a collaborative environment, pairing expert data scientists with nonexperts across the analytic life cycle will be essential to capitalize on the skills of all parties.
- User outreach. Using augmented analytics not only to support new and less expert analytic users, but also to shorten time to insight for more expert users.
- Ecosystem. It will be critical to build an ecosystem that includes not only tools but also data, people and processes to support the use of augmented analytics.

User Recommendations

Data and analytics leaders looking to make analytics more pervasive should:

- Identify the personas that will benefit most from augmented analytics capabilities.
- Ensure users can get value from new augmented analytics features by providing targeted and context-specific training. Invest in data literacy to ensure responsible adoption.
- Focus on explainability as a key feature to build trust in autogenerated models.
- Assess the augmented analytics capabilities and roadmaps of analytics and BI, data science, data preparation platforms, and startups as they mature. Look for upfront setup and data preparation required, the types of data and range of algorithms supported, integration with existing tools, explainability of models and the accuracy of the findings. Also evaluate emerging dynamic data storytelling capabilities.
- Provide incentives for citizen data scientists to collaborate with, and be coached by, specialist data scientists who still need to validate models, findings and applications.

Sample Vendors

Microsoft (Power BI); Oracle (Analytics Cloud); Qlik; SAP Analytics Cloud; SAS; Tableau; Tellius; ThoughtSpot; AnswerRocket; Igenius; Conversight.ai; TIBCO Spotfire

Gartner Recommended Reading

Magic Quadrant for Analytics and Business Intelligence Platforms

Critical Capabilities for Analytics and Business Intelligence Platforms

Tool: Visual Guide to Analytics and Business Intelligence Platform Capabilities

Top Trends in Data and Analytics for 2021

How Augmented Analytics Will Transform Your Organization: A Gartner Trend Insight Report

Natural Language Query

Analysis By: Rita Sallam

Benefit Rating: Moderate

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Definition:

Natural language query allows business users to query data using business terms typed into a search box or via voice. Vendors may use different techniques and vary in terms of analytical complexity of queries, data volumes and types supported. Some use keyword search, and others translate search terms into natural language questions using natural language processing technology. Some use a combination of both. Some support structured data or unstructured data only or a combination of both.

Why This Is Important

- Gartner estimates that adoption of analytics and business intelligence (BI) tools is still limited to about one-third of employees in organizations.
- Despite significant advances in the usability for analysts of the current point-and-click visual-based analytics and BI platforms, this paradigm is still too hard for most business users to ask their own questions.

Business Impact

- NLQ is an increasingly important interface for analytics and BI content creation and analysis to extend access to analytics beyond highly skilled analysts to mainstream business users.
- NLQ can help drive adoption by users resistant to using visual-based BI interfaces for interacting with data, but who are quite comfortable using a search engine to find the information they need.
- NLQ vendors that support queries across both structured and unstructured data can unify fact and context.

Drivers

- While vendors have attempted for some time to bring search and/or natural language query (NLQ) into the analytics and BI context, indexed datasets were often limited. Moreover, the effort and costs to map and model data were too high, the language interpretations were too inaccurate, or the questions supported were too basic to be useful.
- Adoption of NLQ continues to grow as the availability and sophistication is improving with new entrants and new features within existing platforms addressing many of these challenges.
- As demand for pervasive analytics increases, analytics and BI platform vendors have responded by improving their support for and innovation around NLQ. NLQ is rapidly becoming a standard and critical capability of analytics and BI platforms rather than a specialty point solution.
- NLQ is also becoming central to new consumer-oriented user experiences that combine augmented analytics or auto generated insights, narratives and anomaly detection into dynamic data stories and conversational analytics.

Obstacles

- To be useful, NLQ must support how business people ask questions. Limitations can frustrate users by reducing the practical usefulness of NLG for users and therefore hinder adoption for many users.
- Currently, support varies among different vendors for analytically complex queries, data sizes and types, integration with natural language generation tools to explain findings and with automated insights to show the user related findings.
- Capabilities also vary among vendors in terms of support for next questions to ask, spoken languages beyond English, domain and industry ontologies, ease of configuration, and how much needs to be predefined in advance versus dynamically generated.

User Recommendations

Data and analytics leaders looking to make analytics more pervasive should:

- Consider using NLQ to help workers not accustomed to BI tools find the insights and information they need to make decisions.

- Assess the NLQ roadmaps of your existing analytics and BI vendors as well as innovative start-ups and conduct proof of concepts with your data and users. While this capability is becoming less differentiated, vendors support different levels of capabilities maturity and real world usefulness.
- Evaluate how NLQ will fit into the broader business analytics solution architecture and, more widely, how it relates to enterprise search tools (what Gartner now calls insight engines).
- Include IT as a key part of the evaluation and adoption of NLQ-specific vendors and capabilities. These tools often require some level of IT support for deployment, data ingestion integration/modeling/mapping and application development.

Sample Vendors

AnswerRocket; iGenius; Marlabs; Microsoft; Oracle; SAP; Sinequa; Tableau; Tellius; ThoughtSpot

Gartner Recommended Reading

Magic Quadrant for Analytics and Business Intelligence Platforms

Critical Capabilities for Analytics and Business Intelligence Platforms

Tool: Visual Guide to Analytics and Business Intelligence Platform Capabilities

Top Trends in Data and Analytics for 2021

Cloud Analytics

Analysis By: Julian Sun, Austin Kronz

Benefit Rating: Moderate

Market Penetration: More than 50% of target audience

Maturity: Early mainstream

Definition:

Cloud analytics delivers analytics capabilities as a service. It often comprises database, data integration and analytics tools. As cloud deployments continue, the ability to connect to both cloud-based and on-premises data sources in a hybrid model is increasingly important. Cloud-native architecture or multicloud deployments are also becoming popular in order to cater to the cloud ecosystem.

Why This Is Important

There is growing adoption of cloud analytics. Most analytics deployments are originating in the cloud, and the majority of organizations say they are using or plan to use the cloud for analytics and data science. The cloud capability among analytics and BI vendors is also growing with emerging capabilities coming from cloud first. Cloud becomes an ideal place to build modular analytics capabilities that enable greater agility and reuse of existing investments in support of composable business.

Business Impact

- The cloud-enabled composition platform can achieve innovation by assembling modular analytics capabilities.
- More advanced analytics can complement key components of the analytics infrastructure in the cloud. The high computational load due to machine learning in advanced analytics can be carried in the cloud.
- Business users can pilot the cloud-first augmented analytics with an analytics sandbox provisioned by the cloud. It is a faster time to value and more targeted analytics deployment for specific business areas.

Drivers

- To better leverage scalability and elasticity from the cloud, many platforms have rearchitected themselves to be cloud-native.
- To bring more flexibility for organizations that are already using multicloud, vendors are also adding more deployment options and management capabilities. This enables portability with microservices architectures that are readily supported via Kubernetes across multiple clouds.
- Analytics solutions, such as Microsoft Power BI, are attracting 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, which are complementary to established platforms.
- The range of capabilities is growing too. Reporting and data visualization were already commodified capabilities. But customers can now also subscribe to 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.
- The growing cloud DBMS is also helping support and expand this market.

Obstacles

- Security is the No. 1 concern for organizations when moving to the cloud, but organizations need to plan how they will integrate their growing cloud analytics deployments with additional data sources, provide access to third-party analytic tools, and embed analytics in business processes. All of these are in hybrids of on-premises and cloud.
- Organizations' adoption of the cloud is closely tied to data gravity. Data gravity is the concept that as the amount of data grows, and the levels of customization, integration and access needs increase, data has greater propensity 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 their data center of gravity predominantly in on-premises legacy solutions.
- Hype around cloud analytics continues to be high, but is now facing growth obstacles as organizations struggle with deployment challenges.

User Recommendations

- Establish a designed approach to move to the cloud incrementally rather than simply "lift and shift." as cloud analytics is becoming a dominant option in most scenarios in the analytics space.
- Include innovative cloud analytics solutions in their portfolio, renovating components or complementing their on-premises platform if organizations want to gain competitive advantage through Analytics and BI. Completely disregarding cloud analytics solutions means risk for many organizations, as most vendors don't focus their R&D efforts on legacy products.
- Be aware of the extra cost they need to spend and the TCO while adopting other products in the same cloud stack as the vendors are adding new capability in the clouds. From a cost perspective, although not requiring significant upfront investment like on-premises solutions do, cloud analytics solutions will likely have a more expensive licensing cost when considering periods of four or more years.

Sample Vendors

Alibaba Cloud; Sigma Computing; Mode; Microsoft; Oracle; Qlik

Gartner Recommended Reading

Achieve Bimodal Equilibrium With Cloud Analytics

Adopt Cloud Analytics to Drive Innovation

Composable Analytics Shapes the Future of Analytics Applications

Magic Quadrant for Analytics and Business Intelligence Platforms

Critical Capabilities for Analytics and Business Intelligence Platforms

Climbing the Slope

Embedded Analytics

Analysis By: Kevin Quinn, James Richardson

Benefit Rating: High

Market Penetration: 20% to 50% of target audience

Maturity: Early mainstream

Definition:

Embedded analytics are delivered within a user's natural workflow, without the need to toggle to another application. Next-generation embedded analytics capabilities are coming from additional sources outside of analytics and business intelligence (ABI) platforms, including APIs published from artificial intelligence (AI) and data science platforms, and core AI developer services (CAIDS).

Why This Is Important

There is a trend for organizations to invest in the prebuilt domain and industry-specific solutions with embedded analytics. Vendors of embedded analytics technology have promoted no-code and low-code environments based on containers or microservices architecture, respectively. Both are important in a "composable" architecture. Embedded "composable" analytics will enable organizations to create a best-of-breed solution made up of components from vendors across the data and analytics landscape.

Business Impact

Customer-facing departments, like sales and marketing, are often the most interested in leveraging analytics to improve customer experience. Traditional embedded analytics solutions insert reports and dashboards into an application to support decisions. Today, it is as likely that predictive and prescriptive analytics are embedded in a process via an API published by an AI and data science platform. The new landscape for embedded analytics will include vendors from adjacent markets.

Drivers

- **Downward pricing pressure:** There is downward pricing pressure coming from mega vendors like Microsoft and Google. This shrinking price is making embedded analytics functionality accessible to more companies.

- **Trend toward composable architectures:** End-user organizations' move to the cloud and hybrid cloud environments has introduced speedy advancement in container technology and microservices architectures — common characteristics of cloud software and composable architectures. This has enabled organizations to more easily assemble a best-of-breed environment out of pre-existing components.
- **AI and market convergence:** Confidence has grown in leveraging AI and machine learning (ML) to do heavy lifting, that is, processing large amounts of data and leveraging AI and ML techniques to understand key drivers, make predictions and even prescribe the next best action, without anyone ever looking at a report or dashboard. While traditional embedded analytics products have come from the ABI market, this new trend has opened up opportunities for embedded analytics to AI and data science platforms, and core AI developers services vendors.
- **Consumerization of analytics:** Many of the vendors in the ABI space have shifted focus from enabling business analysts to empowering nontechnical end users to ask and answer questions. This introduced a shift away from building tools for designing reports and dashboards to augmented and automated capabilities that empower business end users like natural language interfaces and automated insights. Augmented capabilities that empower nontechnical business users are differentiating features for embedded analytics platforms.

Obstacles

- ABI vendors and embedded analytics vendors have shifted focus away from building reports and dashboards to providing functionality for generating predictive and prescriptive analytics. To do this, they are leveraging AI and ML technologies to augment and automate functionalities like data preparation and insight generation. They are also adding the ability to leverage these technologies from within their tools to provide forward looking analytics. The challenge is that AI and ML technologies are the domain of data science platforms as well as many open-source tools. This has put the two markets on a collision course. End-user organizations are now considering using data science platforms to embed advanced analytics in applications instead of using ABI platforms.
- Besides huge open source libraries of prebuilt components for R and Python, there are libraries of open-source D3 charts that offer the potential for internal development teams to build their own solutions at a much lower cost.

User Recommendations

- Select workplace analytics scenarios of high value and high feasibility associated with current business challenges as a pilot project. Investigate how users want to receive analytics to help them solve problems. Make a list of the functionalities needed to achieve the desired results.
- Compare the capabilities of your enterprise standard for ABI with those identified in your requirements list.
- Investigate vendors from Gartner's Magic Quadrant for Analytics and Business Intelligence as they tend to support embedded analytics. Prioritize platforms that demonstrate advanced analytics capability (including AI and ML), Natural Language Processing (NLP) and automated insights.
- Assess your own organization's ability to leverage data science platforms or open source tools to embed advanced analytics in production applications. This will mean that your organization has a high level of AI and ML maturity, and has produced successful results.

Sample Vendors

GoodData; Infor (Birst); Logi Analytics; Microsoft; MicroStrategy; Oracle; Salesforce; Sisense; Syncfusion

Gartner Recommended Reading

Critical Capabilities for Analytics and Business Intelligence

Magic Quadrant for Analytics and Business Intelligence

Composable Analytics Shapes the Future of Analytics Applications

Tech CEOs: Increase Your Competitive Advantage With the Right Embedded Analytics Platform Provider

Indoor Location Intelligence

Analysis By: Annette Zimmermann

Benefit Rating: High

Market Penetration: 5% to 20% of target audience

Maturity: Adolescent

Definition:

Indoor location intelligence refers to services and solutions that generate, process and analyze data in an indoor environment. They 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, ultrawideband (UWB) and lidar.

Why This Is Important

The two broad use cases for indoor location intelligence are people monitoring and asset tracking, and these can be divided into hundreds of subuses. Since the COVID-19 outbreak, interest in this technology has further accelerated with the proliferation of social distancing solutions. These solutions can include different elements to help employees return to work, such as special tracking devices, analytics software or mobile apps.

Business Impact

We see strongest growth of indoor location intelligence in healthcare, retail and manufacturing, followed by hospitality, public transport/airports and the public sector. Each vertical presents different benefits/impacts for indoor location intelligence. In healthcare, hospitals benefit from asset tracking, patient tracking and monitoring, and staff tracking to increase efficiencies and lower cost, while visitors benefit from indoor navigation and a better customer experience.

Drivers

We have positioned this profile two positions further in the post-trough area. The drivers identified are:

- The COVID-19 pandemic induced proliferation of indoor location intelligence during 2020 as organizations with a lot of external traffic such as retail shops, airports, stadiums, etc., turned to location intelligence to adhere to social distancing guidance.
- Lidar emerged as a new technology to measure distance between assets or people for location intelligence. Some vendors started to integrate lidar into their existing wireless location technology portfolio. Moreover, a growing number of indoor location services platforms integrate with computer vision and CCTV systems to perform people counting and/or measure distance between people.

- New technologies are driving indoor location intelligence forward. For example, 3D mapping and augmented reality wayfinding represent an intersection between location and immersive technologies.

Obstacles

- Technology choice: Some technologies provide centimeter accuracy versus 4 to 5 meters, but 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.

- Data privacy: Location data is sensitive data and needs to be treated as such, especially in an external, client-facing situation. Capture and analysis of location data of visitors in large venues such as shopping centers, museums and stadiums, often requires consent. Also, privacy regulations vary widely in different markets, therefore location data needs to be handled differently in one location compared to another.

User Recommendations

- Be cognizant of the direct trade-off between location accuracy and cost, and deploy the technology that supports your 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 need to collect, store and process, and for what purpose. Set up different scenarios that categorize the data types. These categories should be location data of objects vs. people, and then further refined by anonymized vs. identifying data. This will help you determine which data privacy regime to follow.

- Be transparent toward staff on when and what location data is processed/stored, emphasizing the safety aspects of your solution and the fact that personal location data is not tracked off-premises.

Sample Vendors

AiRISTA Flow; CenTrak; Purple; Quuppa; Ubisense; Zebra Technologies

Gartner Recommended Reading

Magic Quadrant for Indoor Location Services, Global

Competitive Landscape: Indoor Mapping

Market Guide for Indoor Location Application Platforms

Architecting for Location

Self-Service Data and Analytics

Analysis By: Austin Kronz, Joao Tapadinhas, Sharat Menon, Alys Woodward

Benefit Rating: High

Market Penetration: 20% to 50% of target audience

Maturity: Early mainstream

Definition:

Self-service data and analytics refers to technology and processes that business users leverage with minimal involvement from IT departments. Enabled via low-code/no-code tools in areas such as analytics and business intelligence, data preparation and data catalogs, self-service is now moving into other areas of data and analytics as automation and augmentation impact all aspects of D&A.

Why This Is Important

Self-service is established in many organizations as an ideal best practice. It can be a way for organizations to create analytics prototypes and pilot them faster than relying solely on IT for analytics projects. However, organizations must recognize when prototypes require large or real-time data or the need for content to be accessed by many users, as IT support will likely still be required to help implement dedicated data integration pipelines or catalog data and analytics, for example.

Business Impact

Self-service data and analytics is critical to scaling the benefits of data-driven decision making. Emerging citizen analyst or citizen data scientist personas who understand the business context of the data are able to use powerful no-code/low-code analytic platforms to quickly discover insights.

Drivers

- Vendors are building self-service capabilities into their products, but need to make sure they match users' abilities, particularly at the less able end of the spectrum. Vendors have claimed self-service in analytics for decades, but self-service needs superior user interfaces and more data literacy programs to advance.
- As business users advance in terms of information requirements, they expect to be able to extend the use of self-service into data areas. Adding data sources to analytical environments, selecting data sources from data catalogs and integrating data sources from outside the organizations are all tasks that advanced business users (also referred to as power users or citizen developers) expect to be able to do.
- Budgets for purchasing analytics and BI tools are increasingly coming from business units and not just central IT/data teams.

Obstacles

- Governance over self-service tools is a common concern. Modern data and analytics platforms deployed without a plan around user enablement and training typically leads to governance challenges down the road. Aware of this possibility, many organizations overcorrect and do not take advantage of the power of self-service tools, overrestricting who can use them and what they have access to. Organizations need to achieve a balance of agility and control.
- The closer the self-service gets to the data; the greater involvement is required from the data engineering team. Data staff are less aware and understanding of the desire for self-service than analytics staff, because they are typically more concerned about governance and accuracy.
- High quality data is still a struggle for many organizations. Despite having powerful tools, poor data quality can lead to greater potential for misunderstanding or misuse of the data.

User Recommendations

- Segment your users by their ability and inclination to become self-servicing, and deliver to the most prepared users first. Success often snowballs and drives further successes, and aids in improving your D&A maturity over time.
- Evaluate data catalog and self-service data management to allow business users to add curated or external sources to their data landscapes.
- Form communities of self-service users and nonusers alike. Self-service should not be self-serving; communities where sharing, collaboration, education, project overviews and success evangelism become critical as analytics audiences grow.
- Build data literacy and certification programs to ensure users are best prepared to gain productivity improvements from self-service without mistakenly delivering bad or siloed information. Implement self-service for Mode 2 projects with dedicated staff members who have time to focus on learning how to use tools for data management, exploration and analysis.

Sample Vendors

Alteryx; DataRobot; Microsoft; Qlik; Tableau; Trifacta

Gartner Recommended Reading

How to Build a Data Engineering Practice That Delivers Great Consumer Experiences

How to Balance Control and Agility in Your Self-Service Analytics

Create a Hybrid Centralized and Decentralized Data and Analytics Organizational Model

Build a Comprehensive Ecosystem for Citizen Data Scientists to Drive Impactful Analytics

Market Guide for Data Preparation Tools

Tool: Evaluate Data Preparation Tools Across Key Capabilities

The 3 Pillars of Citizen-Driven Data Management

Event Stream Processing

Analysis By: W. Roy Schulte, Pieter den Hamer

Benefit Rating: Transformational

Market Penetration: 20% to 50% of target audience

Maturity: Early mainstream

Definition:

Event stream processing (ESP) is computing that is performed on streaming data (sequences of event objects) for the purpose of stream analytics or stream data integration. ESP is typically applied to data as it arrives (data "in motion"). It enables situation awareness and near-real-time responses to threats and opportunities as they emerge, or it stores data streams for use in subsequent applications.

Why This Is Important

ESP is a key enabler of continuous intelligence and related real-time aspects of digital business. ESP's data-in-motion architecture is a radical departure from conventional data-at-rest approaches that historically dominated computing. ESP products have progressed from niche innovation to proven technology and now reach into the early majority of users. ESP will reach the Plateau of Productivity within several years and eventually be adopted by multiple departments within every large company.

Business Impact

ESP transformed financial markets and became essential to telecommunication networks, smart electrical grids and some IoT, supply chain, fleet management, and other transportation operations. Most of the growth in ESP during the next 10 years will come from areas where it is already established, especially IoT and customer experience management. Stream analytics from ESP platforms provides situation awareness through dashboards and alerts, and detects anomalies and other significant patterns.

Drivers

Five factors are driving ESP growth:

- Companies have ever-increasing amounts of streaming data from sensors, meters, digital control systems, corporate websites, transactional applications, social computing platforms, news and weather feeds, data brokers, government agencies and business partners.
- Business is demanding more real-time, continuous intelligence for better situation awareness and faster, more-precise and nuanced decisions.

- ESP products have become widely available, in part because open-source ESP technology has made it less expensive for more vendors to offer ESP. More than 40 ESP platforms or cloud ESP services are available. All software megavendors offer at least one ESP product and numerous small-to-midsize specialists also compete in this market.
- ESP products have matured into stable, well-rounded products with many thousands of applications (overall) in reliable production.
- Vendors are adding expressive, easy-to-use development interfaces that enable faster application development. Power users can build some kinds of ESP applications through the use of low-code techniques and off-the-shelf templates.

Obstacles

- ESP platforms are overkill for most applications that process low or moderate volumes of streaming data (e.g., under 1000 events per second), or do not require fast response times (e.g., less than a minute).
- Many ESP products required low-level programming in Java, Scala or proprietary event processing languages until fairly recently. The spread of SQL as a popular ESP development language has ameliorated this concern for some applications, although SQL has limitations. A new generation of low-code development paradigms has emerged to further enhance developer productivity but is still limited to a minority of ESP products.
- Many architects and software engineers are still unfamiliar with the design techniques and products that enable ESP on data in motion. They are more familiar with processing data at rest in databases and other data stores, so they use those techniques by default unless business requirements force them to use ESP.

User Recommendations

- Use ESP platforms when conventional data-at-rest architectures cannot process high-volume event streams fast enough to meet business requirements.
- Acquire ESP functionality by using a SaaS offering, IoT platform or an off-the-shelf application that has embedded CEP logic if a product that targets their specific business requirements is available.
- Use vendor-supported closed-source platforms or open-core products that mix open-source with value-added closed-source extensions for mainstream applications that require enterprise-level support and a full set of features. Use free, community-supported, open-source ESP platforms if their developers are familiar with open-source software and license fees are more important than staff costs.
- Use ESP products that are optimized for stream data integration to ingest, filter, enrich, transform and store event streams in a file or database for later use.

Sample Vendors

Amazon; Confluent; Google; IBM; Informatica; Microsoft; Oracle; SAS; Software AG; TIBCO Software

Gartner Recommended Reading

Market Guide for Event Stream Processing

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

Market Share Analysis: Event Stream Processing (ESP) Platforms, Worldwide, 2020

In-DBMS Analytics

Analysis By: Henry Cook

Benefit Rating: High

Market Penetration: 20% to 50% of target audience

Maturity: Early mainstream

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 modeling, operations and model scoring — down into the DBMS platform, close to the data, in order to reduce data movement and support rapid analysis.

Why This Is Important

In-DBMS analytics provides agility, productivity and a robust way of getting ML results into production — all of which are desirable. They are also relatively new to cloud DBMS systems; once organizations get up to speed on the new in-DBMS analytics capabilities, their use will increase.

Business Impact

In-DBMS analytics provides a robust way of developing advanced analytics, such as machine learning and artificial intelligence. They provide an ideal vehicle for moving machine learning models into production and monitoring their effectiveness. This increases the productivity of the developers, makes them more agile and means that machine learning can more readily be productionized. This makes the data science process more efficient and delivers increased business benefits.

Drivers

- In-DBMS analytics offerings have been available from on-premises data warehouse software vendors for many years and are now increasingly featured in cloud DBMS which is increasing acceptance and adoption.
- Machine learning is becoming more commoditized as its use spreads beyond specialist data scientists, in-DBMS machine learning is an excellent enabler for this wider group of developers and users.
- Most of today's DBMS vendors are offering in-DBMS analytics capabilities with various ML libraries. Some analytics vendors such as SAS and IBM (SPSS software) can push their analytics processing down into a suitable DBMS. Also, some vendors such as Alteryx and Fuzzy Logix provide analytics libraries that can be used with DBMS from more than one vendor.
- The drive for greater productivity in the use of machine learning, ease of administration and the need to reliably move machine learning into production is encouraging adoption. Adopting in-DBMS analytics provides a very good solution for moving analytic models to production with model generation, administration and execution all in the same environment.

Obstacles

- There has been a lack of familiarity with data management tools, including DBMSs, among data scientists plus a lack of familiarity with ML among DBMS professionals. Data scientists have tended to prefer R, Python, and notebooks (Jupyter, Apache Zeppelin), DBMS practitioners SQL.
- In-DBMS analytics requires a sufficient range of analytical algorithms. This is now much easier than was previously possible, and in fact is becoming the norm. However, using organizations still need to validate how they will fit into their overall estate and most importantly how the analytics will be monitored and controlled.
- Some implementations are restricted in performance and their ability to scale. To be used at scale the algorithms do not just need to be made available but to be modified to take advantage of parallel processing. This is not a problem with most offerings, but needs to be checked in a proof of concept prior to adoption.

User Recommendations

Data and analytics leaders should:

- Contemplate in-DBMS analytics as a viable option for making large-scale business analytics available to a wider audience. In-DBMS analytics embeds machine learning capabilities in familiar 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.
- Review your data science development process. Evaluate whether it can be better enabled through in-DBMS analytics, especially for deployment which can be much easier with in-DBMS analytics.
- Check whether in-DBMS analytics is supported when evaluating DBMS systems and, if so, the range of algorithms offered. Experiment with use cases where it is more efficient bringing ML algorithms to the data at scale.

Sample Vendors

Fuzzy Logix; Google; IBM; Micro Focus; Oracle; SAP; Teradata; VMware

Gartner Recommended Reading

5 Useful Ways to Use Artificial Intelligence and Machine Learning With Your Logical Data Warehouse

Magic Quadrant for Data Science and Machine Learning Platforms

Magic Quadrant for Cloud Database Management Systems

Why In-DBMS Analytics Deserves a Fresh Look

Social Analytics

Analysis By: Melissa Davis

Benefit Rating: Moderate

Market Penetration: 20% to 50% of target audience

Maturity: Early mainstream

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.

Why This Is Important

Most data and analytics leaders are aware of the marketing, sales and customer service use cases. However, other capabilities may also be relevant. Social analytics tools are used for a variety of purposes, including HR, product, risk management and supply chain. Social analytics use cases can include:

- Keyword monitoring
- Measuring campaign success
- Competitive analysis
- Influencer analysis
- Identifying market trends
- Reputation monitoring
- Crisis management
- Collecting customer feedback

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. Examples include:

- Product teams can analyze market feedback to understand product use and if new product categories are emerging.
- Marketers can measure the impact of advertising campaigns or uncover new target markets for their products.
- Analysts can identify early warning signals like sources of customer satisfaction and process breakdowns.

Drivers

Adoption of Social Analytics Across the Enterprise

- The use of social analytics applications in marketing or market research is well-established. Social analytics applications supporting broader use cases (in customer support, for example) are less common but readily available from a technology perspective.
- CX analytics vendors will most likely build or buy pieces of social analytics functionality.
- Social media marketing suites will be most important by providing multichannel analytics and publishing capabilities.

Growing Diversity of Data Sources Analyzed Beyond Text, Including Image, Call Center Audio and Video

- Social media analytics started with, and continues to be based on, text analytics. But image analytics is becoming increasingly important. When applied to social media analytics, image analysis is an extension of text analytics features applied to visual context. Increasingly, vendors are moving from basic logo recognition and analytics text captions to recognizing multiple elements within an image. Their ability to go beyond logos to include faces, activities, objects and scenes, and video analysis means they can analyze the “why” behind a behavior, not just “what” behavior occurred. Video analytics is currently supported by very few vendors, as it is not yet proven. However, the broader and more diverse the data analyzed, the more potential value in the insights.

Increased Adoption of Advanced Analytics, Including AI technologies

- Many vendors have advanced their offerings from basic rule-based keyword searches to apply natural language processing (NLP), artificial intelligence (AI) and machine learning (ML) to enhance sentiment analysis, analyze patterns across the buying and owning journey, and predict outcomes.

Obstacles

- 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.
- Social analytics is often managed by a social media team rather than a broader analytics team that can support marketing, product development, sales, CRM or HR.
- Data availability is lacking. Although Facebook has the most active users, it's data is very restricted and therefore represents only a small slice of data available to social analytics tools to analyze.
- There are concerns about violent, politically charged, extremely misleading or other kinds of content that attracts the scrutiny of citizens, law enforcement and governments.

User Recommendations

- Collect use cases by deciding which application categories you need and what information sources are important. Identify first and secondary priority use cases to help evaluate tools based on your unique needs.
- Create a business case around revenue generated, cost savings or risk reduction by prioritizing business outcomes by stakeholders.
- Work with your main analytics, BI, data science and CX vendors to understand how they may ingest social data from social analytics applications and platforms. Ask them if data from other applications — such as voice of the customer (VoC) — can be integrated to make data more valuable.
- Explore image, video, audio and sentiment analysis in addition to text analytics. Evaluate vendors via their proofs of concept (POCs) across each social analytics use case as capabilities vary among vendors.
- Validate vendor selections by requesting three to five customer references to obtain the user's perspective on potential solution providers during an RFI/RFP process.

Sample Vendors

Black Swan Data; Brandwatch (acquired by Cision); Clarabridge; Khoros; ListenFirst; Netbase Quid; Sprinklr; Sprout Social; Talkwalker; Zignal Labs

Gartner Recommended Reading

Market Guide for Social Analytics Applications

Demystifying Social Analytics

Text Analytics

Analysis By: Shubhangi Vashisth, Stephen Emmott

Benefit Rating: Moderate

Market Penetration: 20% to 50% of target audience

Maturity: Early mainstream

Definition:

Text analytics is the process of deriving business insight or automation from structured and unstructured 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.

Why This Is Important

Text analytics addresses a diverse range of uses, from general capabilities to extracting data from textual content, to industry-specific and line of business (LOB) use cases. Vendors in this market provide products that extract meaning and context from textual content. This can then be used to derive insights and action, either within the context of the product or by other products to which the data is made available.

Business Impact

Text analytics, when combined with various other analytics capabilities, can benefit the organization in the following areas:

- Preprocessing unstructured data for analysis.
- 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 Q&A).

- Sentiment (analyzing notes, social media or transcripts to identify the author's attitude about a subject).

Drivers

Key drivers include:

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

Text analytics uses different combinations of technologies for different business use cases:

- Healthcare — medical records analysis by mapping key medical 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 — monitoring product pricing across markets
- 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

Obstacles

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 organizations 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.
- Most organizations lack a strategy to deal with semistructured and/or unstructured data. The approach to select tools for point solutions adds to the problem of tool sprawl.
- Training the solutions for specialized use cases is also a barrier in adoption.

User Recommendations

- Position text analytics as an NLT in the context of internal discussions so its role in augmentation and automation can be correctly framed.
- Identify and prioritize use cases that text analytics can address, and create an enterprise text analytics strategy.
- Review the text analytics market to acquaint yourself with its vendors, products and capabilities.
- Start with prepackaged products designed for business users to administer for well-established use cases, such as the voice of the customer (VoC). Cloud-based text analytics packages also offer a good way to experiment and enable easy adoption of the technology.
- Select products based on how well they suit specific business scenarios and their ability to integrate with other applications that work with unstructured data, such as conversational agents.
- Allow a realistic lead time to recruit text analytics talent. Consider working with a third-party analytics service provider for text analytics initiatives.

Sample Vendors

Amazon Web Services; Amenity Analytics; Bitext; Clarabridge; Google; IBM; Lexalytics; Megaputer; Microsoft; Proxem; SavantX

Gartner Recommended Reading

Artificial Intelligence Primer for 2021

Market Guide for Text Analytics

Toolkit: Supporting Data for the Selection of Text Analytics Vendors

Understanding Your Customers by Using Text Analytics and Natural Language Processing

Entering the Plateau

Logical Data Warehouse

Analysis By: Henry Cook, Adam Ronthal

Benefit Rating: High

Market Penetration: More than 50% of target audience

Maturity: Early mainstream

Definition:

The logical data warehouse (LDW) is a best-practice analytics data management architecture design that combines multiple physical analytics engines into a logically integrated whole. Data and analytics leaders can use the LDW to cover the full range of modern analytic requirements with a logically unified system that provides a simple view of all their data without needing to copy the data.

Why This Is Important

The LDW architecture is a current best practice for analytical systems design. It enables users to accommodate a wide variety of user types, data types, data sources and analytical techniques: SQL, OLAP, Graph, Geospatial, machine learning, statistical and others. The LDW integrates the traditional data warehouse, data lake and other analytical systems into a cohesive whole. This allows users to be more agile and productive while meeting their demanding service levels.

Business Impact

By accommodating a wide variety of users, data and analytical processing, the LDW architecture enables organizations to maximize their return on investment in analytics. In addition, the modular LDW architecture builds in a variety of flexible choices that can address both current and future needs.

Drivers

- Modern analytics requirements need to support many types of data, analytical processing techniques, types and numbers of users, and service levels. Designers can meet these requirements by integrating multiple analytic servers and services using data virtualization, data transports and common metadata to achieve a single logical view of all data.

- The LDW enables enhanced enterprise agility and maximizes return on investment for both development and runtime. It does this by ensuring that there is a natural home for each requirement, in terms of data storage and processing. This minimizes the need to change the architecture to meet new requirements. This makes development and deployment easier and more productive.
- Using the right component for each requirement processing is done with maximum efficiency and minimum cost. This also contributes to maximum return on investment.

Obstacles

Architecture skills are needed when building a system based on the LDW architecture:

- The appropriate components need to be chosen and integrated, typically using common metadata, data virtualization and data transport mechanisms.
- Architects need to be able to identify the correct components and interfaces to meet functional, performance and scalability needs.

Obstacles to adoption have diminished recently due to the adoption of the principles of the LDW architecture by most vendors:

- It is now common for the data warehouse and data lake components of the LDW to be preintegrated.
- The architect's job is further aided by advancements in key enabling technologies such as active metadata, data management automation, and improved DBMS performance and scaling.
- Likewise, relevant best practices are now better understood for data architecture and logical modeling.

User Recommendations

Data and analytics leaders should:

- Adopt an LDW architectural approach — this has emerged as a best practice for data management in analytics environments.

- Expect to build the LDW incrementally. It is not necessary to build the entire system at once. All that is required is to anticipate likely future components and preposition the necessary interfaces.
- Use the LDW architecture to also resolve the tension between the need for agile experimentation and prototyping and the need to accommodate the more stringent acceptance criteria for more traditional querying and reporting.
- Leverage the LDW to address challenges that can be solved via a logical integration approach, such as distributed data, time-sensitive data, and volatile environments where sources, targets and datasets come and go frequently.

Sample Vendors

Amazon Web Services; Cloudera; Databricks; Denodo; IBM; Microsoft; Oracle; Snowflake; Teradata

Gartner Recommended Reading

Solve Your Data Challenges With the Data Management Infrastructure Model

The Practical Logical Data Warehouse

6 Things to Get Right for the Logical Data Warehouse

Market Guide for Analytics Query Accelerators

5 Useful Ways to Use Artificial Intelligence and Machine Learning With Your Logical Data Warehouse

Organizing Your Teams for Modern Data and Analytics Deployment

Magic Quadrant for Cloud Database Management Systems

Critical Capabilities for Cloud Database Management Systems for Analytical Use Cases

Outdoor Location Intelligence

Analysis By: Bill Finnerty

Benefit Rating: High

Market Penetration: More than 50% of target audience

Maturity: Mature mainstream

Definition:

Outdoor location intelligence (OLI) is the process of deriving meaningful insight from geospatial data relationships — people, places or things — to solve particular challenges like demographic analysis, store placement, asset tracking, people movement and contact, environmental analysis. and traffic planning. OLI consists of a combination of GIS software, web mapping solutions, geospatial services and platforms, position technologies such as GPS, and location-based data.

Why This Is Important

Location is one of the most significant means of contextualizing user and sensor data. OLI, founded in geospatial and location intelligence, presents an ever-growing set of use cases in marketing, smart cities, Industrie 4.0, healthcare and other sectors.

Cloud, whether PaaS or SaaS, and web mapping solutions provide expanded opportunities for organizations to leverage and scale OLI at competitive prices, making the entry point for experimentation within reach of a larger number of organizations.

Business Impact

OLI can reveal previously unidentified opportunities, based on location and spatial relationships, for business and government. Opportunities manifest as improved operations, new approaches to marketing and engagement, and enhanced decision making. Cases can be found across many sectors, including government, retail, hospitality and transportation — for example, combining business and location data to visualize customer and revenue data on maps to identify sales and marketing opportunities.

Drivers

- Increasing amounts of spatially contextualized data, frequently generated by IoT sensors, provides enhanced opportunities to leverage geospatial and location intelligence to improve service, engagement and decision making. Access to this spatial data through open data portals, data marketplaces and location intelligence platforms is growing, generating more opportunities for its use.

- Maturing OLI tools increasingly support business line functionality. In addition to GIS vendors and those embedding OLI in applications, business intelligence and other data visualization solutions regularly provide OLI capabilities. Solutions frequently enable “citizen analysts” to leverage OLI data for spatial analysis to improve operations, discover new business and service delivery opportunities, and communicate with customers and constituents.

- Through the growth of location intelligence platforms, a larger number of organizations are able to use machine learning capabilities to analyze the vast amount of spatial data available to them. These machine learning capabilities are driving the development of more-advanced location intelligence solutions, such as improved routing and traffic analysis that benefits commuters, logistics companies and public safety organizations.

Obstacles

- Privacy and data laws, although being challenged as part of the pandemic response, require organizations to be mindful of their use of personal data in OLI initiatives or face societal backlash.

- The cost of data can price projects without a clear ROI beyond an organization’s reach. However, data-as-a-service offerings can provide some controls.

User Recommendations

- Empower business units in leveraging OLI by providing the platform to improve decision making, service delivery and business processes.
- Inspire business stakeholders to leverage OLI in new ways by providing relative examples and use cases, while also insisting that they clearly define the business value or ROI for any initiatives.
- Establish a spatial data management strategy, or include spatial data in an existing data strategy, to improve quality and use of spatial data. Use the strategy to expose data catalogs to maximize data reuse and promote data sharing.
- Include spatial data in existing data governance processes.
- Create a framework for determining the best means for acquiring data. Include options for using open data, developing new datasets, utilizing data as a service or purchasing new data.
- Grow the skills of citizen analysts to improve understanding of spatial analysis and relative capabilities by establishing a spatial data and analysis training program.

Sample Vendors

Alteryx; CARTO; Descartes Labs; DECE Software; Esri; HERE Technologies; Mapbox; Microsoft; Planet; Qlik

Data and Analytics Services

Analysis By: Jorgen Heizenberg, Twiggy Lo

Benefit Rating: High

Market Penetration: 20% to 50% of target audience

Maturity: Mature mainstream

Definition:

Data and analytics services are consulting, system integration and managed services for the management of data for all uses (operational and analytical) and the analysis of data to drive business processes and improve business outcomes through more effective decision making. The core capabilities include D&A strategy, data management, analytics and BI, data science and machine learning, D&A governance, program management, and enterprise metadata capabilities.

Why This Is Important

Organizations are deploying D&A to support enterprise digital transformation and acceleration. As a result, the use of D&A is becoming more strategic and expanding across business units with decentralized D&A communities. Most organizations lack the time and the skills to execute on these D&A initiatives, and this is driving engagement with external service providers to fill in the skills gaps and deliver rapid time to transformation.

Business Impact

- **Chief Data Officer:** Gartner's sixth annual CDO Survey shows that 83% of respondents' enterprises had digital transformation initiatives; nearly a quarter (23.8%) were leading the transformation initiatives; 72% were either leading or heavily involved.

- **Domain D&A Leaders:** Gartner's 2020 The Rise of Business-Domain-Led Data and Analytics Survey finds that leading organizations have shifted from traditional, centralized, IT-centric D&A teams to a model where domain D&A leaders share responsibility.

Drivers

- Organizations beginning their data-driven transformation, expanding D&A in their digital business strategies and becoming adept at maximizing the value of their D&A assets will see the greatest impact from external D&A services. Clients turn to service providers for their best practices, depth of (technical and business) expertise, improved time to market and faster value realization.

- Organizations moving to a more fact-based approach for decisions and/or business process transformation supported by D&A will need a life cycle of planning, building, managing, governing and optimizing D&A solutions delivered by external service providers.

- Organizations looking to scale and industrialize AI and machine learning technologies — beyond experimenting and innovating — will need support to improve accuracy, trustworthiness, and speed of their pilots and prototypes as they move toward production.

- Service providers are rapidly adopting an “asset-based consulting” model that uses intellectual property assets for particular industries or business domains and prebuilt automation to accelerate delivery. These IP assets can include reusable code, frameworks, tools, methodologies, preconfigured solutions and platform-based business solutions. Automation ranges from basic macros and scripts to full-fledged AI, cognitive computing and machine learning.

Obstacles

- Many service providers are active in this market, and D&A leaders find it increasingly difficult to differentiate between them.

- Enterprises increasingly expect D&A service providers to drive organizational performance and guide digital business, but some lack the capabilities to do so.

- Offerings of external D&A service providers are generally well-established; however, some areas, like machine learning, and innovation areas like data monetization and data sharing, still need skills improvement.

- External D&A service providers also need to build up skills for new approaches like DataOps, MLOps (aka XOps) and data fabric.

- Other areas that would benefit from expansion of skills are D&A governance and ethics, as well as change management and data literacy.

User Recommendations

To evaluate how to best use external D&A service providers, organizations should:

- Identify the D&A deficit (needed external support) based on the type of initiative, such as D&A strategy, data management, data governance or analytics programs.
- Collaborate with business stakeholders to prioritize requirements for external D&A skills, industry experience and technology support.
- Identify the types of intelligent automation and consulting assets, and change management capabilities required to embed D&A in the business processes and workflows of their organizations.
- Develop a set of D&A performance metrics, derived from the business stakeholder objectives, to measure the impact of the external services on the organization's business outcomes.

Sample Vendors

Accenture; EPAM; EXL; Fractal Analytics; SDG Group; West Monroe

Gartner Recommended Reading

Magic Quadrant for Data and Analytics Service Providers, Worldwide

Critical Capabilities for Data and Analytics Service Providers, Worldwide

Tool: Vendor Identification for AI and Data and Analytics Service Providers

Tool: RFP Template for Engaging With Data & Analytics Service Providers

Predictive Analytics

Analysis By: Peter Krensky

Benefit Rating: High

Market Penetration: 20% to 50% of target audience

Maturity: Early mainstream

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.

Why This Is Important

Predictive analytics were in early mainstream adoption before the COVID-19 pandemic and adoption has only accelerated since. Early adopters have proven and refined use cases with clear value. Most organizations have numerous initiatives underway related to predictive analytics and plenty of organizations are just getting started. Additionally, client searches on gartner.com for “predictive analytics” continue to trend upward.

Business Impact

Predictive analytics prioritizes identifying and providing an understanding of likely future outcomes to enable improved decision making as well as threat/opportunity identification. As a result, organizations can be proactive rather than reactive (for example, predictive maintenance of equipment, demand prediction, fraud detection and dynamic pricing). Interest and investment continue to grow in both new use cases and more traditional applications of predictive analytics.

Drivers

Levels of project underperformance and ROI failure are low, and this technology is on the doorstep of the Plateau of Productivity. Though related AI and ML innovations remain highly hyped, this profile’s journey on the Hype Cycle is nearly at an end. The value derived from predictive analytics is well-aligned with expectations. Interest continues to be driven by improved availability of data, lower-cost compute processing (especially in the cloud) and a growing body of 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. Additional drivers of predictive analytics hype and adoption include:

- Lessons learned from the COVID-19 pandemic on the need for agile and adaptable predictions
- Application developers leveraging pretrained models and cloud AI services to add predictive analytics to applications
- Embedded predictive analytics in enterprise applications and other software

- Augmented analytics capabilities and support for low-code/no-code model building
- Education and upskilling programs for citizen data scientists and augmented consumers
- Growing numbers of practicing expert data scientists
- Emerging roles such as ML engineer and chief data scientist

Obstacles

- Poor data quality/availability combined with data engineering burden placed on data scientists
- Technical debt (deploying predictive models without proper consideration of ongoing maintenance costs and need for IT support)
- Properly defining, designing and supporting XOps (MLOps, ModelOps, DataOps, PlatformOps, etc.)
- Talent recruitment, development, retention and organization
- Predictive model value estimation and project prioritization, and ongoing collaboration with consumers of predictive analytics
- Reliance on black-box models, and evolving standards and regulations around model explainability and bias detection

User Recommendations

- Expect to manage a heterogeneous portfolio across multiple analytics communities.
- Evaluate the buy option first. Predictive analytics can be quite easy to deploy and use if delivered via a packaged application or a cloud AI developer 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.
- Build solutions either through an external service provider, or with skilled in-house staff using a combination of open-source technologies and a data science platform.
- Use a combination of these tactics (buy, build, outsource) and explore vendors with offerings that combine two or more of these approaches.
- Focus on an operationalization methodology, including ML engineering roles, formal processes and investment in vendor platforms in the initial stages of planning.

Gartner Recommended Reading

Magic Quadrant for Data Science and Machine Learning Platforms

Critical Capabilities for Data Science and Machine Learning Platforms

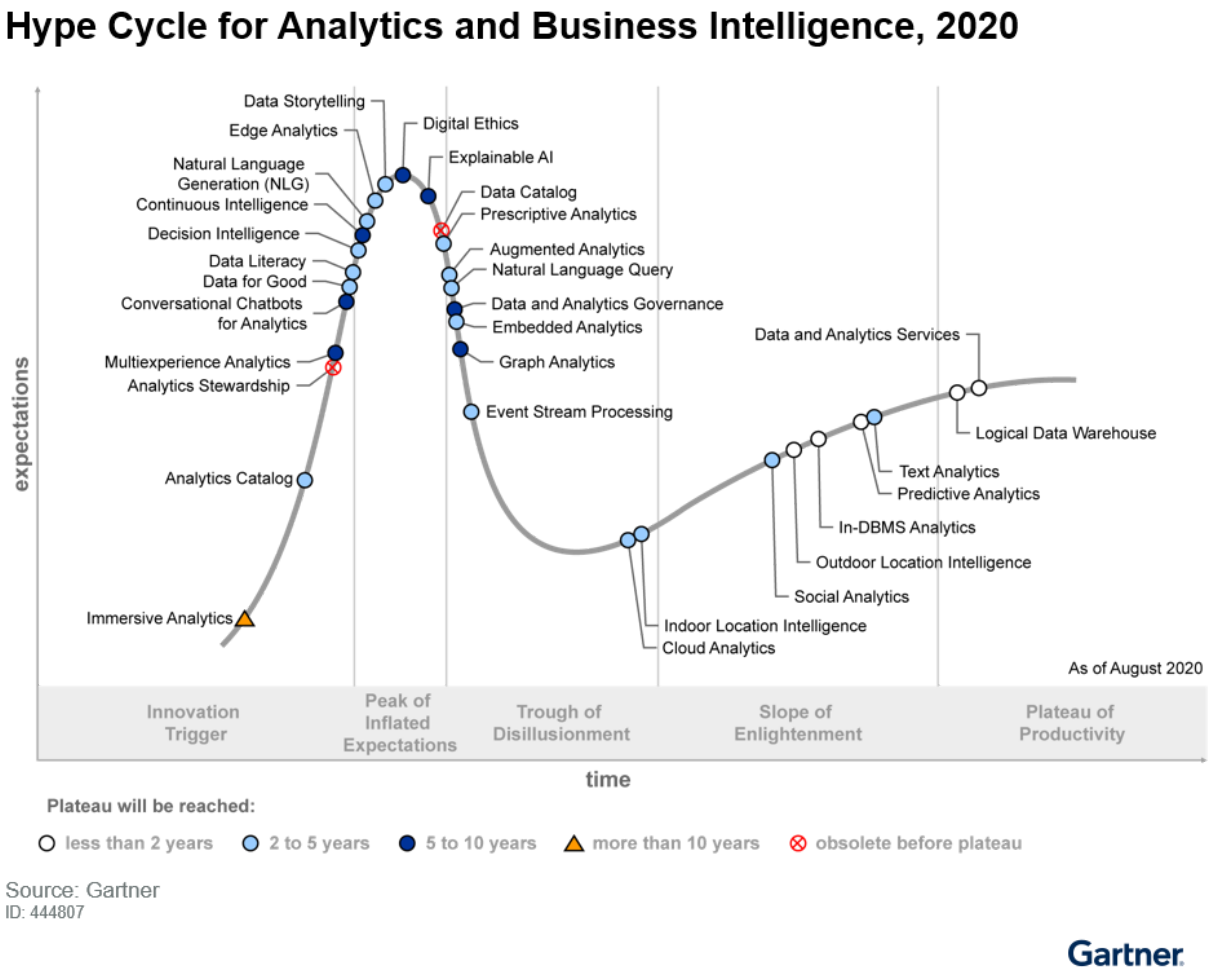
Maximize the Benefits of Augmented Analytics With a Strategic Action Plan

Top Trends in Data and Analytics for 2021: The Rise of the Augmented Consumer

When and How to Combine Predictive and Prescriptive Techniques to Solve Business Problems

Appendixes

Figure 2: Hype Cycle for Analytics and Business Intelligence, 2020



Source: Gartner (August 2020)

Hype Cycle Phases, Benefit Ratings and Maturity Levels

Table 2: Hype Cycle Phases

(Enlarged table in Appendix)

Phase ↓	*Definition* ↓
Innovation Trigger	A breakthrough, public demonstration, product launch or other event generates significant media 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 innovation is pushed to its limits. The only enterprises making money are conference organizers and content publishers.
Trough of Disillusionment	Because the innovation 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 innovation's applicability, risks and benefits. Commercial off-the-shelf methodologies and tools ease the development process.
Plateau of Productivity	The real-world benefits of the innovation 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 innovation to reach the Plateau of Productivity.

Source: Gartner (July 2021)

Table 3: 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 2021)

Table 4: Maturity Levels

(Enlarged table in Appendix)

Maturity Levels ↓	Status ↓	Products/Vendors ↓
Embryonic	In labs	None
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 2021)

Evidence

[1] See Top Trends in Data and Analytics for 2021.

Document Revision History

Hype Cycle for Analytics and Business Intelligence, 2020 - 5 August 2020

Hype Cycle for Analytics and Business Intelligence, 2019 - 18 July 2019

Hype Cycle for Analytics and Business Intelligence, 2018 - 20 July 2018

Hype Cycle for Analytics and Business Intelligence, 2017 - 28 July 2017

Hype Cycle for Business Intelligence and Analytics, 2016 - 25 July 2016

Hype Cycle for Business Intelligence and Analytics, 2015 - 4 August 2015

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

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Understanding Gartner's Hype Cycles

Create Your Own Hype Cycle With Gartner's Hype Cycle Builder

Top Trends in Data and Analytics for 2021

Worlds Collide as Augmented Analytics Draws Analytics, BI and Data Science Together

Market Guide for Augmented Analytics Tools

Premises Switching Equipment: Rest of Western Europe, 2002

IT Score for Data & Analytics

Table 1: Priority Matrix for Analytics and Business Intelligence, 2021

Benefit	*Years to Mainstream Adoption*			
↓	***Less Than 2 Years*** ↓	***2 - 5 Years*** ↓	***5 - 10 Years*** ↓	***More Than 10 Years*** ↓
Transformational		Augmented Analytics Citizen Data Science Continuous Intelligence Decision Intelligence Event Stream Processing	Composable D&A	
High	Data and Analytics Services In-DBMS Analytics Logical Data Warehouse Outdoor Location Intelligence Predictive Analytics	Data Literacy Data Storytelling Edge Analytics Embedded Analytics Indoor Location Intelligence Natural Language Generation Prescriptive Analytics Self-Service Data and Analytics	Conversational Analytics Data Marketplaces and Exchanges Explainable AI Graph Analytics ModelOps	
Moderate		Cloud Analytics Data & Analytics for Good Natural Language Query Social Analytics Text Analytics	Analytics Catalog Immersive Analytics Multiexperience Analytics	

Benefit	*Years to Mainstream Adoption*			
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