# Hype Cycle for Data Science and Machine Learning, 2021

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Initiatives: Analytics, BI and Data Science Solutions

Accelerated digitization is driving the urgency to productize experimental data science and machine learning initiatives. Data and analytics leaders must analyze the evolution of existing and emerging trends to orchestrate and productize DSML.

# Analysis

## What You Need to Know

There are two major drivers within data science and machine learning (DSML): democratization to make DSML accessible to more personas (power users and consumers, corporate developers, and citizen data scientists) within the enterprise and operationalization to help reap business value faster by bridging deployment gaps.

Gartner sees major innovations coming from corporate research labs, open-source communities and academia. Organizations have set up teams specifically for development and application of cutting-edge machine learning techniques. These technologies aim to support model operationalization, build adaptive systems, increase contextual awareness and drive decision intelligence in the enterprise.

There are additional Hype Cycles for 2021 that will help data and analytics (D&A) leaders form a holistic view of D&A:

- Hype Cycle for Analytics and Business Intelligence, 2021
- Hype Cycle for Data Management, 2021
- Hype Cycle for Data and Analytics Governance and Master Data Management, 2021
- Hype Cycle for Artificial Intelligence, 2021
- Hype Cycle for Natural Language Technologies, 2021
- Hype Cycle for Customer Experience Analytics, 2021

## The Hype Cycle

Organizations see that data science and ML play a key part in their digital transformation, which is driven by the following trends:

- Collision: One of the biggest trends in this space is driven by the collision and convergence of neighboring technologies, roles, disciplines and so on. As the lines blur, especially between conventional analytics and data science, organizations are able to leverage different methods to drive decision intelligence.

- Composability: The ability to “compose” a fit-for-purpose approach for organization needs is dominating a one-size-fits-all approach. Technologies such as graph analytics, feature stores, transfer learning, composite AI, and data labeling and annotation services are improving the way DSML systems are designed and leveraged.
- Resilience: The COVID-19 pandemic exposed shortcomings in the DSML processes that are now being systematically addressed. Small and wide data and ModelOps, along with AI trust, risk and security management (AI TRiSM), are emerging trends that are being used to build a resilient enterprise.

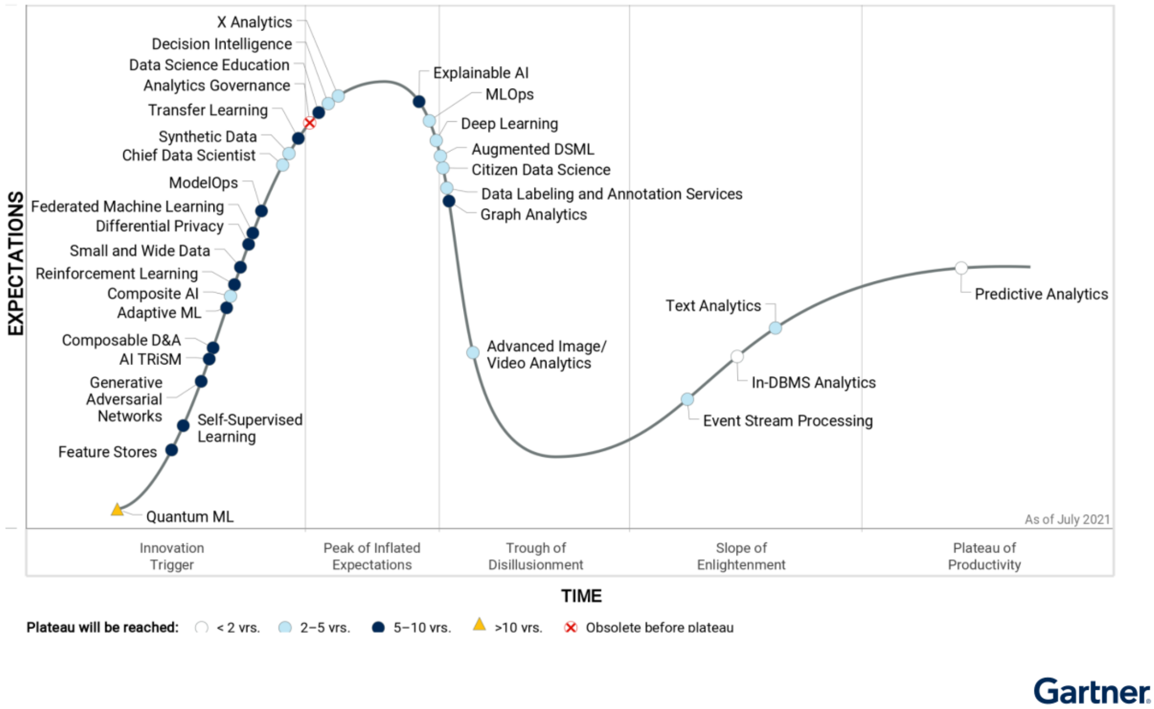
Predictive analytics, event stream processing, data labeling and annotation services, and differential privacy were fast movers on the Hype Cycle this year in comparison to last year.

The Peak of Inflated Expectations remains densely populated with clustered technologies because of active research in the area. This is driving not only differentiation, but also considerable hype.

Several technologies are either on or climbing toward the Plateau of Productivity, most notably predictive analytics, text analytics and in-DBMS analytics, which have advanced rapidly due to extensive usage. Apache Spark and Notebooks no longer appear on the HC because they are now widely adopted.

We’re seeing multiple technologies gaining momentum that are still over five years away from the Plateau of Productivity. It is exceptional to have both a bare peak and trough in this year’s Hype Cycle, which translates to the beginning of the second wave of DSML hype.

**Figure 1: Hype Cycle for Data Science and Machine Learning, 2021**




Source: Gartner (August 2021)

Downloadable Graphic: Hype Cycle for Data Science and Machine Learning, 2021

## The Priority Matrix

The Priority Matrix arranges each innovation profile by its level of benefit attainable versus its predicted time to plateau. The darker the color, the more attention D&A leaders should pay (generally) to those innovations.

Innovations of transformational benefit will reduce dependence on traditional data scientists and lower the barriers to starting data science projects, but it will not reduce the needs for validation and governance. As more techniques are offered prepackaged as services, making them accessible to a variety of personas will offer disruptive potential across industries. Composable D&A will allow organizations to have flexibility and heterogeneity in their DSML systems.

Innovations of high benefit will have a significant impact on data science programs during the next two to five years and will help organizations address a wider spectrum of use cases. Organizations will also demand more explainability of the outcomes of ML initiatives, not just from a compliance perspective, but also to foster more trust, manage risks and ensure transparency in the deployed models.

### Table 1: Priority Matrix for Data Science and Machine Learning, 2020

(Enlarged table in Appendix)

| Benefit | Years to Mainstream Adoption | | | |
|---|---|---|---|---|
| | Less Than 2 Years | 2 - 5 Years | 5 - 10 Years | More Than 10 Years |
| Transformational | | Advanced Image/Video Analytics<br>Augmented DSML<br>Citizen Data Science<br>Composite AI<br>Decision Intelligence<br>Deep Learning<br>Event Stream Processing | Adaptive ML<br>Composable D&A<br>Generative Adversarial Networks<br>Self-Supervised Learning | Quantum ML |
| High | In-DBMS Analytics<br>Predictive Analytics | Chief Data Scientist<br>MLOps<br>Synthetic Data<br>X Analytics | AI TRiSM<br>Data Science Education<br>Differential Privacy<br>Explainable AI<br>Federated Machine Learning<br>Graph Analytics<br>ModelOps<br>Reinforcement Learning<br>Small and Wide Data<br>Transfer Learning | |
| Moderate | | Data Labeling and Annotation Services<br>Text Analytics | Feature Stores | |
| Low | | | | |

Source: Gartner (August 2021)

## Off the Hype Cycle

Since this Hype Cycle is intended to provide insight into only the most important and prevalent concepts in the field of DSML, the following entries featured in Hype Cycle for Data Science and Machine Learning, 2020 have been removed from this year's edition. However, a few remain relevant and important in the field of analytics and appear in other Hype Cycles:

- **AI C&SI Services:** The AI Consulting and System Integrator Services is now off this Hype Cycle and is covered separately in Magic Quadrant for Data and Analytics Service Providers.

- **AutoML:** This has been subsumed by Augmented DSML; full, general-purpose, end-to-end automated machine learning (autoML) is only applicable for narrow applications and use cases.
- **Prescriptive Analytics:** This entry is now subsumed within Composite AI.
- **Large-Scale Pretrained Language Models:** This entry has been removed because it is more relevant to the Hype Cycle for Natural Language Technologies, 2021.
- **Kubeflow:** This technology is now subsumed under MLOps and subsequently ModelOps.
- **Apache Spark and Notebooks**: These technologies have moved beyond the Plateau of Productivity into mainstream adoption.

## On the Rise

### Quantum ML

**Analysis By:** Chirag Dekate, Martin Reynolds

**Benefit Rating:** Transformational

**Market Penetration:** Less than 1% of target audience

**Maturity:** Embryonic

#### Definition

Quantum machine learning is a type of machine learning that uses quantum computing techniques to potentially accelerate training of ML systems. Currently, only a limited number of quantum ML algorithms exist, with no confirmed evidence of speedup.

#### Why This Is Important

Theoretically, quantum machine learning (quantum ML) enables a subset of ML algorithms to be run on an entirely new computing paradigm — quantum computing. We have yet to see any evidence that ML could benefit from quantum computing over traditional alternatives. However, the parallel nature of some ML techniques could make quantum computing a viable path to explore.

Increasing awareness of quantum ML capabilities plays a key role in determining its potential value.

#### Business Impact

Quantum ML continues to be in an embryonic stage, with most R&D activities clustered around devising quantum algorithms for key ML kernels. However, the scale of the systems and algorithms and the challenges associated with “data loading” will limit adoption in the near term. Potential applications of quantum computing in artificial intelligence and ML include quantum search, recommendation algorithms, quantum algorithms for game theory, and quantum algorithms for decisions and learning.

#### Drivers

- Early research in developing quantum ML initially indicated the potential for applicability across a growing set of ML algorithms, including k-means, k-medians, hierarchical clustering, principal component analysis, neural networks, support vector machines, nearest neighbors, regression and boosting.

- However, new research in this ever-evolving field seems to call into question the potential applicability of quantum computing in ML. Additionally, considerable hardware and software challenges remain.
- R&D today is focused on developing different quantum algorithms for ML kernels. Vendors such as IBM have prototype ML algorithms implemented for very select use cases.
- Developing scalable ML systems will require many qubits and fundamental advances in applicable quantum algorithms.

#### Obstacles

While quantum ML is theorized to work effectively in noisy intermediate-scale quantum (NISQ) computers, it is not ready for mainstream adoption today. Key obstacles include:

- A nascent quantum computing ecosystem — Quantum computing is still at a very early stage of development, with many systems offering scaling limited to tens of qubits. As a result, algorithms executed on these systems are primarily exploratory in nature.
- Data encoding — Although quantum computing can hypothetically deliver dramatic boosts for certain classes of data, one of the challenges is encoding input data. For quantum ML to work at scale, large amounts of data must be encoded and loaded into the quantum system.
- Lack of mature algorithms — New algorithms that can take advantage of capabilities offered by near-term noisy quantum systems will need to be discovered.

#### User Recommendations

Data and analytics leaders seeking to leverage risk-minimized quantum ML should:

- Reinvest budget in your classical ML ecosystems, where the value return will be demonstrably higher than in simulated quantum environments. Explore quantum ML environments at your own risk.
- Increase your awareness of quantum computing capabilities and the potential for applicability in ML use cases by exploring early quantum ML algorithm prototypes on current systems.

- Prepare for quantum ML by partnering with quantum computing solution providers and consulting experts to devise new ML algorithm kernels.
- Leverage quantum-as-a-service capabilities for validating hypotheses involving quantum ML to minimize risk and maximize the accessibility of quantum computing resources.

### Sample Vendors

D-Wave; Google; IBM; Microsoft Corporation; Pennylane; Xanadu

### Gartner Recommended Reading

Predicts 2021: Disruptive Potential During the Next Decade of Quantum Computing

Innovation Insight for Quantum Computing for the Automotive Industry

Cool Vendors in Quantum Computing

## Feature Stores

**Analysis By:** Georgia O'Callaghan

**Benefit Rating:** Moderate

**Market Penetration:** 1% to 5% of target audience

**Maturity:** Emerging

### Definition

Feature stores are solutions built to address the need for data reusability, reproducibility and reliability in machine learning (ML) portfolios. They consist of a repository of data curated for ML, known as features, with accompanying metadata, such as versioned transformation code. Training and testing datasets are pulled from the feature store, accelerating ML model development. Some have capabilities for orchestrating feature transformations and monitoring data serving models in production.

### Why This Is Important

Feature stores aim to break down analytical silos, promote collaboration, reduce time spent on feature engineering and enable the reusability of features. A common understanding of how data was transformed to create features can increase consistency, trust and explainability. Feature stores increase the reliability of data serving models in production by providing a consistent view of features across development and production environments, reducing the risk of training-serving skew.

### Business Impact

Feature stores scale to support organizations as they expand ML portfolios and develop a more complex array of ML use cases and requirements. They accelerate ML model development by providing a means to pull datasets for training and testing. They accelerate time to production and ensure data reliability by providing a consistent view of features across development and production environments. They support model audit and retraining, as datasets can be recreated with point-in-time correctness.

Drivers

- Organizations want to expand their use of ML but find that data scientists spend more time sourcing and preparing data to create training and test datasets than developing the ML models.
- Features are the inputs to ML models; they provide the context the algorithm needs for analysis and learning. Due to the time, effort and skill put into selecting and engineering features for ML, they are some of the most highly curated and refined data assets in the business. Despite this, most organizations lack an effective feature management system.
- There can be considerable overlap in features used by ML models, and therefore, the ability to reuse these features across models would lead to faster development times. However, feature engineering within data science teams is typically a siloed practice, occurring on individual machines. Organizations need a mechanism to break down these analytical silos to enable the reusability of features across ML workloads.
- Organizations are increasingly concerned with reproducibility, explainability, audit and governance of ML. Siloed feature engineering efforts make it very difficult to capture the lineage of features and other metadata that would enable these efforts.
- Organizations want to leverage ML models in production, yet the process of recreating and implementing data pipelines in a production environment is prone to issues like training-serving skew.
- Issues like data drift, outliers, poor data quality and missing data can impact model performance. Organizations understand the importance of monitoring ML model performance, however many lack the means to monitor data serving models in production.

### Obstacles

- The feature store has been defined differently by industry leaders, creating confusion and a lack of standardized capabilities. Some vendors focus on solution completeness and others on optimizing specific capabilities. As the term grows in popularity, many vendors now market old solutions as feature stores.
- Vendor solutions have not reached the maturity of plug-and-go tools that can be downloaded and easily installed. Some offerings require the enterprise to have existing infrastructure in place. In other cases, vendors are heavily involved in the initial setup and integrating the solution into the existing technology stack.
- Feature stores are typically supported by two separate database technologies, one optimized for scalability (offline feature store) and the other for low-latency retrieval (online feature store). Despite this, it’s unclear how performance for complex, real-time transformation and serving use cases may be impacted by increasing throughput demands.

### User Recommendations

- Deliver a consistent view of data across development and production environments by storing curated features in a repository that meets requirements for storage scalability and low-latency retrieval of features.
- Increase the efficiency of ML model development by providing data scientists with a searchable catalog of features within the repository, enabling their reuse across ML workloads. Include a means to pull datasets from the repository for training and testing models.
- Increase the reproducibility of features for ML by capturing version-controlled transformation logic, which establishes a clear lineage of features.
- Facilitate model audit and retraining by cataloging metadata that defines datasets used to develop a model so this can be recreated.
- Prevent ML model degradation by monitoring data and automating the detection of problems known to impact performance, such as data drift, outliers, poor data quality and missing data.

### Sample Vendors

Feast; Iguazio; Kaskada; Logical Clocks; Molecula; Scribble Data; Splice Machine; StreamSQL; Tecton

### Gartner Recommended Reading

Feature Stores for Machine Learning (Part 1): The Promise of Feature Stores

Feature Stores for Machine Learning (Part 2): Current State and Future Directions

## Self-Supervised Learning

**Analysis By:** Pieter den Hamer, Erick Brethenoux

**Benefit Rating:** Transformational

**Market Penetration:** Less than 1% of target audience

**Maturity:** Embryonic

### Definition

Self-supervised learning is an approach to machine learning in which labeled data is created from the data itself, without having to rely on historical outcome data or external (human) supervisors that provide labels or feedback. It is inspired by the way humans learn through observation, gradually building up general knowledge about concepts, events and their relations or spatiotemporal associations in the real world.

### Why This Is Important

Self-supervised learning aims to overcome one of the biggest drawbacks of supervised learning: the need to have access to typically large amounts of labeled training data. This is not only a practical problem in many organizations with limited relevant data or where manual labeling is prohibitively expensive. It is also a more fundamental problem with current AI, in which even learning simple tasks requires a huge amount of data, time and energy.

### Business Impact

Self-supervised learning enables the extended applicability of machine learning to organizations that do not have labeled training datasets available. It may also shorten training time and improve the robustness and accuracy of models. Its relevance is most prominent in computer vision, natural language processing, IoT analytics/continuous intelligence, robotics or other AI applications that rely on unstructured data or typically unlabeled sensor data.

### Drivers

- Making ML feasible in the absence of labeled training data: in self-supervised learning, labels can be generated from relatively limited data. In essence, this is done by masking elements in the available data (e.g., a part of an image, a sensor reading in a time series, a frame in a video or a word in a sentence) and then training a model to “predict” the missing element. Thus, the model learns how one part relates to another, how one situation (captured through video and/or other sensors) typically precedes or follows another and which words often go together, for example. In other words, the model increasingly represents the concepts and their spatial, temporal or other relations in a particular domain. This model can then be used as a foundation to further fine-tune the model (e.g., using “transfer learning”) for one or more specific tasks with practical relevance.

- Self-supervised learning can help to derive more value from the still growing availability of Internet of Things sensor data and other diverse, possibly external, sources of data. Taken alone, these data sources (e.g., visual, sound, pressure, temperature or textual data) may be of limited value. More value can be derived from data by identifying associations between data sources, in essence, using the elements or events in one source to label elements or events in another source (see also the use of ‘X analytics’ in ‘small and wide data’).

- A step toward broader AI with more efficient learning: self-supervised learning has the potential of bringing AI closer to the way humans learn. This occurs mainly from observation and association, building up general knowledge about the world through abstractions and then using this knowledge as a foundation for new learning tasks, thus incrementally building up ever-more knowledge that in future AI scenarios may serve as ‘common sense.’

### Obstacles

- Self-supervised learning has only recently emerged from academia and is currently only practiced by a limited number of innovative AI companies. Skills and experience are still very scarce.

- Open source ML frameworks, such as Tensorflow and Pytorch, have started to support self-supervised learning — but tool support is still limited, which makes implementation a knowledge-intensive and low-level coding exercise.

### User Recommendations

- Today, self-supervised learning should only be applied when the importance of the application justifies the risks of a still experimental approach. Scarce, highly experienced ML experts are needed to carefully design a self-supervised learning task, based on masking of available data, which allows a model to build up knowledge and representations that are meaningful to the business problem at hand.
- Organizations should apply self-supervised learning when manual labeling or annotating of data is too expensive or infeasible for other reasons — but only after comparing alternative approaches, such as the use of (external) data labeling and annotations services, synthetic data, reinforcement learning, active learning or federated learning.
- Organizations should monitor the development of self-supervised learning. Once more mature, self-supervised learning has the potential of becoming a pervasively used foundation for a next generation of applications with AI and machine learning.

### Sample Vendors

Craftworks; Google; Helm.ai; Microsoft

### Gartner Recommended Reading

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

Top Trends in Data and Analytics for 2021: Smarter, More Responsible and Scalable AI

Tech Providers 2025: Why Small Data Is the Future of AI

Key Actions to Prevent Machine Learning Failure Due to COVID-19-Related Data Drift

## Generative Adversarial Networks

**Analysis By:** Brian Burke, Svetlana Sicular, Avivah Litan

**Benefit Rating:** Transformational

**Market Penetration:** Less than 1% of target audience

**Maturity:** Embryonic

### Definition

A generative adversarial network (GAN) is a machine learning (ML) technique in which a representation of artifacts from the data is used to generate brand-new, completely original artifacts that preserve a likeness of the original data. GANs are composed of two neural network models, a generator and an opposing discriminator, which learn to produce totally novel media content, synthetic data and models of physical objects.

### Why This Is Important

GANs can generate original objects by imitating learned objects. The power to generate objects provides significant opportunities and risks. GANs can augment humans in many creative, design and discovery processes, and create synthetic data for training other ML models. GANs are also used for creating deepfakes, which are a major risk for business and society. GANs are at the leading edge of artificial intelligence (AI) research and will have a transformational impact during the next few years.

### Business Impact

GANs have the potential to:

- Disrupt the pharmaceutical, manufacturing, media, entertainment, fashion, architecture, engineering and construction industries, as well as any industry that relies on material science
- Augment media content creation activities and design disciplines across industries
- Have a cross-industry impact on marketing and data science roles
- Disrupt business and society with deepfakes (i.e., fake news, nonconsensual pornography and fraud)

### Drivers

Since their inception in 2014, GANs have become incredibly sophisticated. Much of the research has been focused on generating images, often of human faces with increasing fidelity, which have become virtually indistinguishable from real human faces. The potential for misuse of the technology is great, and, in late 2020, the U.S. government passed the “Identifying Outputs of Generative Adversarial Networks (IOGAN) Act” to research technical means to identify generated media. Although deepfakes are a proven risk and are most prevalent today in “revenge porn,” there are many transformational commercial use cases for GANs beyond images, including:

- **Media Content:** Includes (1) text generators for marketing copy, news stories, poetry, resumes, etc., (2) images that can be generated for logos, human images for modeling and landscape images, (3) music or voice that can be generated with a preferred genre or to mimic a person, (4) Video with simulated presenters/models [e.g., training, news, fashion, multilingual], and (5) video game backgrounds; virtual and augmented reality to reduce time/costs.
- **Synthetic Data:** Augments or creates training data for AI models and/or to protect privacy
- **Generative Design for Manufacturing:** Creates multiple design options for parts
- **Generative Design for Architecture:** Creates multiple design options for buildings
- **Material Science:** Develops new materials targeting specific properties
- **Drug Design:** Reduces costs and time in drug discovery

### Obstacles

GANs are difficult to train, unstable and often fail to converge due to training the generator and the discriminator together. The inherent instability makes GANs less than ideal for generative AI, because there are alternative methods that are more stable.

- GANs can create many design options, but a human is still needed to select from the options (optioneering) leading to decision-making paralysis and frustration. Critics argue that the work effort to generate many options and evaluate those options exceeds the work effort to craft a small number of great options by hand.
- GAN-generated objects may be subject to undervaluation by society broadly, because the perceived value of human created objects is likely to be higher than computer-generated objects.
- Deepfakes generate negative press and perceptions around GANs, which can deter investments in GAN research and create regulatory risks.
- Deepfake GAN detection rates will become increasingly difficult.

### User Recommendations

- Organizations with high-risk-tolerance should evaluate the potential for leveraging this technology today, partnering with universities to conduct proofs of concept (POCs), where the potential benefits and drawbacks are significant.
- Technology innovation leaders should do their due diligence and consider the fact that, although the core technologies are readily available in the public domain, the technology is brittle, resource hungry and requires significant (and rare) AI skills.
- Focus on other pressing issues such as explainability; GANs are "black boxes," and there is no way to prove the accuracy of the objects produced other than by subjective methods.

### Sample Vendors

Amazon; Apple; DeepMind; Google; IBM; Insilico Medicine; Microsoft; Neuromation; NVIDIA

### Gartner Recommended Reading

Predicts 2021: Artificial Intelligence and Its Impact on People and Society

Innovation Insight for Generative AI

How to Benefit From Creative AI — Assisted and Generative Content Creation

Top 10 Strategic Technology Trends for 2020: AI Security

Innovation Tech Insight for Deep Learning

## AI TRiSM

**Analysis By:** Avivah Litan

**Benefit Rating:** High

**Market Penetration:** 1% to 5% of target audience

**Maturity:** Emerging

### Definition

AI trust, risk and security management (AI TRiSM) ensures AI model governance, trustworthiness, fairness, reliability, efficacy, security and data protection. This includes solutions and techniques for model interpretability and explainability, AI data protection, model operations, and adversarial attack resistance.

### Why This Is Important

AI poses new trust, risk and security management requirements that conventional controls don't address. Enterprises must implement a disciplined structured AI TRiSM approach to benefit from AI models that improve their business goals. AI models that are deployed in production should be subject to the right checks and balances to ensure sustained value generation. A set of risk and security controls, and trust enablers, must be deployed and continuously used to govern and manage the AI life cycle.

### Business Impact

- Organizations who do not manage AI risk are much more likely to experience negative AI outcomes. Models will not perform as intended, because of either benign mistakes and process errors or malicious interference by bad actors.
- Organizations will make suboptimal business decisions due to AI misperformance. Worst case, malicious interference in AI will result in security failures, financial and reputation loss, and social harm from incorrect, manipulated, unethical or biased AI outcomes.

Drivers

- AI poses considerable data compromise risks, as large, sensitive datasets are often used to train AI models and are shared across organizations. Access to confidential data needs to be carefully controlled to avoid adverse regulatory, commercial and reputational consequences.
- AI risk and security management poses new operational requirements that are not well-understood, and which are not addressed by existing management systems.
- AI models drift for many different reasons and if not constantly monitored and validated, they can generate adverse unforeseen results with severe societal, ethical and operational consequences.
- AI models and data must be constantly monitored to ensure compliance, fairness and ethical implementations. Risk management measures can and should identify and eliminate bias from training data and AI algorithms.
- AI model explainability must be constantly tested to ensure original explanations and interpretations of AI models hold up during model operations. If they don't, corrective actions must be taken.
- Detecting and stopping adversarial attacks on AI requires new methods that are not available from most enterprise security systems.
- Regulations for AI risk management, such as SR 11-7: Guidance on Model Risk Management from the Federal Reserve Bank of the U.S., is driving U.S. financial services to institute measures for managing AI model risk.

**Obstacles**

- AI trust, risk and security management is an afterthought. Organizations generally don’t consider it until models are in production.
- Most AI threats are not well-understood and are therefore not effectively addressed.
- Compliance is the main driver for AI TRiSM, but nonregulated industries have the same threats and issues as regulated sectors do. Regulated sectors, such as financial services and healthcare, are most likely to put in concrete measures to address AI TRiSM.
- AI trust, risk and security management requires a cross-functional team to work together on common goals, using common frameworks. This includes staff from legal, compliance, security, privacy, IT, data analytics and AI model development.
- Integrating life cycle controls is difficult but must be done as part of a comprehensive AI TRiSM program.
- Some toolsets, such as open-source tools for model explainability, need customization to work effectively in the enterprise environment.

### User Recommendations

- Set up an organizational task force or dedicated unit to manage your AI TRiSM efforts. Include members throughout the organization who have a vested interest in your organization's AI projects — for example, from legal, privacy, security, risk, data analytics and AI development.
- Work across your organization to effectively manage best-of-breed toolsets (assuming your AI platform does not fulfill all requirements) as part of a comprehensive AI TRiSM program.
- Rightsize AI models for explainability or interpretability using open-source tools or vendor solutions that add value.
- Implement solutions that protect data used by AI models and prepare to use different methods for different use cases and components thereof.
- Incorporate risk management into model operations by using solutions that assure both model and data integrity, and that constantly validate reliable operations of both.
- Adopt specific AI security tools to ensure adversarial attack resistance and AI model resilience.

### Gartner Recommended Reading

Use Gartner's MOST Framework for AI Trust and Risk Management

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

### 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

### Adaptive ML

**Analysis By:** Pieter den Hamer, Erick Brethenoux

**Benefit Rating:** Transformational

**Market Penetration:** Less than 1% of target audience

**Maturity:** Emerging

#### Definition

Adaptive machine learning (ML) is the capability of frequently retraining ML models when online in their runtime environment, rather than only training ML models when offline in their development environment. This capability allows ML applications to adapt more quickly to changing or new real-world circumstances that were not foreseen or available during development.

#### Why This Is Important

Adaptive ML gets AI much closer to self-learning, or at least to more frequent learning, compared with most current AI applications, which only use static ML models that depend on infrequent redeployment of new model updates to improve themselves. Its main benefit is to respond more quickly and effectively to change, enabling more resilient and ultimately autonomous systems that are responsive to the dynamics of both gradual change and massive disruptions.

#### Business Impact

Adaptive ML is most relevant in areas in which the context and conditions, or the behavior or preferences, of actors change persistently. It is also used to fine-tune, contextualize or personalize models once in production. Example application areas include customer churning in highly competitive markets, gaming, organized crime fighting and anti-terrorism, fraud detection, cybersecurity, quality monitoring in manufacturing, virtual personal assistants, semiautonomous cars, and smart robotics.

Drivers

- The ever-increasing complexity, pace and dynamics in the environment, society, and business require ML models that frequently adapt to changing circumstances and impactful events. This is most relevant in real-time application areas like continuous intelligence, streaming analytics, decision automation, and augmentation in a myriad of industries and business areas. Less frequent model updates can already be achieved by the current ML approach of offline retraining, using the full set of available training data and periodic model update deployments.

- With adaptive ML, models remain accurate longer and suffer less from model drift. Data science teams can improve their productivity by leveraging adaptive ML to reduce the need for conventional model monitoring, retraining, redeployment or “MLOps.”

- Adaptive ML can be used to compensate for limited availability of training data or “small data,” hindering offline (for example, supervised or reinforcement) learning during development. Adaptive ML may start out with a minimal viable model that was pretrained offline, with the model then incrementally improved or fine-tuned during the actual online usage. For this reason, adaptive ML is also known as continual or continuous learning. For example, reinforcement learning may be done in a simulated environment during development and continued in a real environment during production.

- Adaptive ML allows for the personalization or contextualization of ML models, using a more general ML model as a starting point and then adjusting this to the preferences of their user or the specifics of their operating environment.

- Combined with federated or swarm ML, adaptive ML can benefit from model improvements in multiple locations and usage contexts. Together, these approaches are a key enabler of ultimately autonomous systems, such as self-driving vehicles or smart robots, which should be able to demonstrate resilience in their ever-changing contexts.

### Obstacles

- Adaptive ML depends on the availability of feedback from users, operating environment or closed loop data about the quality of the ML output (for example, prediction errors) while online.
- With adaptive ML there is no time for repeated full retraining of the model but only for incremental retraining while online. This requires incremental learning algorithms that must be tuned in terms of weighting new data versus older data that was used for earlier online or offline training. Other challenges include the prevention of overfitting and proper testing and validation, at least periodically.
- The specific way to implement adaptive ML may vary per use case and training algorithm, with tool and open source framework support only just emerging.
- Nontechnical challenges include ethical, reliability, liability, safety and security concerns that come with self-learning and autonomous systems.

### User Recommendations

- Organizations should consider adaptive ML not to replace but to complement current ML. Most adaptive ML applications will start out with a model that was first trained offline. Adaptive ML can be seen as a way to further improve, maintain, contextualize, personalize or fine-tune the quality of ML models once online.
- Accompany adaptive ML with model monitoring for accuracy and relevancy and also with proper risk analysis and risk mitigation activities, if only to frequently monitor the quality and reliability of adaptive ML applications. Even with adaptive ML, a periodic offline full retraining of the model may be required, as incremental learning has its limitations.
- Organizations should actively manage the required talent, infrastructure and enabling technology. For example, adaptive ML is likely to be more demanding in terms of compute power in runtime environments and will require the development of knowledge about new (incremental learning) algorithms and tools.

### Sample Vendors

Guavus; IBM; Microsoft; SAS Institute; Sony; Tazi

### Gartner Recommended Reading

Emerging Technologies: Critical Insights for Adaptive Machine Learning

Key Actions to Prevent Machine Learning Failure Due to COVID-19-Related Data Drift

Use Gartner's 3-Stage MLOps Framework to Successfully Operationalize Machine Learning Projects

Innovation Insight for Continuous Intelligence

AI Security: How to Make AI Trustworthy

### Composite AI

**Analysis By:** Erick Brethenoux, Pieter den Hamer

**Benefit Rating:** Transformational

**Market Penetration:** 5% to 20% of target audience

**Maturity:** Emerging

#### Definition

Composite AI refers to the combined application of different AI techniques to improve the efficiency of learning to broaden the level of knowledge representations and, ultimately, to solve a wider range of business problems in a more efficient manner.

#### Why This Is Important

Composite AI is currently mostly about combining "connectionist" AI approaches like machine learning (ML), with "symbolic" and other AI approaches like rule-based reasoning, graph analysis, agent-based modeling or optimization techniques. The ideas behind composite AI are not new. The goal is to enable AI solutions that require less data and energy to learn and which embody more "common sense." Composite AI recognizes that no single AI technique is a silver bullet.

#### Business Impact

Composite AI offers two main benefits. First, it brings the power of AI to a broader group of organizations that do not have access to large amounts of historical or labeled data but possess significant human expertise. Second, it helps to expand the scope and quality of AI applications (that is, more types of reasoning challenges can be embedded). Other benefits, depending on the techniques applied, include better interpretability and resilience and the support of augmented intelligence.

Drivers

- Limited availability of data, or small data, has pushed organizations to combine multiple AI techniques. Where raw historical data has been more scarce, enterprises have started to complement it using additional AI techniques such as knowledge graphs and generative adversarial networks (GANs) to generate synthetic data.
- Combining AI techniques is much more effective than relying only on heuristics or a fully data-driven approach. A heuristic or rule approach can be combined with a deep learning model (for example, predictive maintenance). Rules coming from human experts or the application of physical/engineering model analysis may specify that certain sensor readings indicate inefficient asset operations, which can be used as a feature to train a neural network to assess and predict the asset's health.
- The democratization of computer vision solutions is also a driver of this technology. In computer vision, (deep) neural networks are used to identify or categorize people or objects in an image. This output can be used to enrich or generate a graph, which represents the image entities and their relationships, answering questions like which object is in front of another, what the speed of an object is and so on. Using an ML approach only, such simple questions are very hard to answer.
- Agent-based modeling is the next wave of composite AI. In supply chain management, for example, a composite AI solution can be composed of multiple agents, each representing an actor in the ecosystem, with its own sensors to monitor local conditions and ML to make predictions. Combining these agents into a "swarm" enables the creation of a common situation awareness, more global planning optimization and more responsive scheduling.
- ML- and analytics-based AI techniques often lead to insights informing actions. In addition, the most appropriate actions can be further determined by combinations of rule-based and optimization models — a combination often referred to as prescriptive analytics.

### Obstacles

- The lack of knowledge relevant to leverage multiple AI techniques could prevent organizations from considering the techniques particularly suited in solving specific problem types.
- If the methods, best practices and platforms are starting to adequately address the MLOps domain (that is, the operationalization of ML models), the ModelOps domain (that is, the operationalization of multiple AI models, such as optimization models, rules models and graph models) remains an art much more than a science. A robust ModelOps approach will be necessary to efficiently manage and govern composite AI environments, not to mention its harmonization with other disciplines such as DevOps and DataOps.
- The AI engineering discipline is also starting to take shape, but only mature organizations have started to apply its benefits in operationalizing AI techniques. Security, ethical model behaviors, models autonomy and change management practices will have to be addressed across the combined AI techniques.

### User Recommendations

- Identify projects in which a fully data-driven, ML-only approach is inefficient or ill-fitted. For example, this is the case when not enough data is available or when the required type of intelligence is very hard to represent in current artificial neural networks.
- Leverage domain knowledge and human expertise to provide context to and complement data-driven insights by applying decision management with business rules, knowledge graphs or physical models in conjunction with machine learning models.
- Combine the power of machine learning in data science, image recognition or natural language processing with graph analytics to add higher-level, symbolic, spatiotemporal and relational intelligence.
- 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.

### Sample Vendors

ACTICO; BlackSwan Technologies; Exponential AI; FICO; IBM; Indico Data Solutions; Petuum; SAS Institute

### Gartner Recommended Reading

Top Strategic Technology Trends for 2021: AI Engineering

How to Use Machine Learning, Business Rules and Optimization in Decision Management

How to Use AI to Fight COVID-19 and Beyond

How to Manage the Risks of Decision Automation

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

## Reinforcement Learning

**Analysis By:** Alexander Linden, Shubhangi Vashisth, Farhan Choudhary

**Benefit Rating:** High

**Market Penetration:** Less than 1% of target audience

**Maturity:** Embryonic

### Definition

Reinforcement learning (RL) is a type of machine learning where the learning system receives training only in terms of rewards and punishments. It then attempts to foster actions or situations for which the overall reward is maximized and the punishments are minimized.

### Why This Is Important

Some problems can only be solved with reinforcement learning, especially when other ML approaches are failing due to a lack of training data.

### Business Impact

Its primary potential is in industrial control and gaming industries. However, since the technology can deliver incremental efficiency improvements on complex automated processes, it may also lead to significant improvements for self-driving cars, robotics, vehicle routing, warehouse optimization, logistics, predictive maintenance and other industrial control scenarios.

### Drivers

- Recent successes in text summarization and machine translation, real-time bidding for marketing and advertising, creation of dynamic treatment regimes in healthcare, media and entertainment and gaming industries.
- Commercial vendors coming up with RL components (Microsoft's acquisition of Bonsai, and Amazon SageMaker RL, AWS DeepRacer, NVIDIA DRIVE) and semicommercial institutions' activities (e.g., OpenAI).
- Fascination with the RL framework which involves much less training data and supervision than currently dominant, supervised learning schemes.
- Faster compute capabilities.
- Better simulation capabilities.

### Obstacles

- Limited RL capabilities offered by current DSML platforms.
- High computational requirements.
- Lack of good-enough simulations in many business situations.
- Solutions are often brittle or difficult to implement.
- Experienced staff is rare.
- Lack of explainability.

### User Recommendations

- Be cautious to apply RL only when the business outcomes and constraints are clear, but you lack sufficient data to build robust ML models.
- Acquire special expertise, because the application of RL is currently riskier than more traditional techniques.
- Leverage off-the-shelf capabilities available from vendors such as, but not limited to, Google, Amazon, Microsoft and other smaller vendors to take advantage of RL in business applications.

### Sample Vendors

Amazon Web Services (AWS); Dataiku; OpenAI

### Gartner Recommended Reading

3 Types of Machine Learning for the Enterprise

Innovation Tech Insight for Deep Learning

## Small and Wide Data

**Analysis By:** Jim Hare, Pieter den Hamer, Svetlana Sicular

**Benefit Rating:** High

**Market Penetration:** 1% to 5% of target audience

**Maturity:** Emerging

### Definition

Small data is about the application of analytical techniques that require less data but still offer useful insights. Wide data enables the analysis and synergy of a variety of small, large, unstructured and structured data sources. Together these approaches apply a variety of data augmentation techniques such as X analytics, simulation, synthetic data, transfer learning, federated learning, self-supervised learning, few-shot learning and knowledge graphs.

### Why This Is Important

Analytics and AI need to be able to use available data more effectively, either by reducing the required volume or by extracting more value from unstructured and diverse data sources. Small and wide data approaches enable more robust analytics, reducing dependency on big data and helping attain a more complete situational awareness or 360-degree view. This enables organizations to make analytics more resilient in the increasingly complex context of disruptions and evolving customer demands.

### Business Impact

Small and wide data techniques help make analytical and machine learning models more resilient to disruptions. Small data is helpful for AI problems, where big datasets are not available, by applying less data-hungry techniques, synthetic approaches or by augmenting data through the synergy with unstructured, external or synthetic data sources. Wide data uses a broader variety of data sources to increase context and situational awareness for both human decision makers and AI applications.

### Drivers

- Disruptions such as the COVID-19 pandemic have resulted in many production AI models across different industry verticals losing accuracy and relevance because they were trained using past big data that reflected how the world worked before the pandemic hit. Retraining models using the same approach was not feasible, because more recent data, just a few weeks old, was too limited to reflect the patterns of the new market circumstances.

- Organizations continue to struggle when getting started with AI projects if there is not enough volume or variety of data available to find the relevant model features or training datasets for complex models.

- Decision making is also becoming more complex and demanding, requiring a greater variety of data for better situational awareness and/or detecting rare events.

- More mature organizations that already implemented solutions for which they have enough data want to solve unique, differentiating problems where they need to overcome data size and variety limitations.

### Obstacles

- Lack of tools and user skills needed to link disparate datasets across different data formats to uncover new insights or add more context to existing business decision making.
- Misperception that AI projects require large datasets before organizations can get started, resulting in lost productivity and delayed deployments.
- Organizations waiting until production AI models encounter accuracy issues rather than proactively incorporating small and wide data techniques early on as part of the model life cycle process.
- Confusion or lack of understanding about which small and wide data techniques are best for specific classes of AI problems.
- Nascent emerging techniques such as zero-, one- and few-shot learning that require specialized skills.
- Small data techniques are fragmented; they address specific challenges, such as only image analysis, only tabular data or only exclusively algorithmic side, rather than addressing the small and wide data issues overall.

### User Recommendations

- Explore small data and algorithmic approaches to increase model resilience and lower the barrier to entry for AI. Data techniques include data and feature enrichment and expansion via synthetic data, external data sources, metadata, graphs, etc. Algorithmic techniques include generative AI (GANs, few-shot learning) and composite AI.
- Enrich and improve the predictive power of data by incorporating a greater variety of structured and unstructured data sources. These formats include tabular, text, image, video, audio, voice, temperature, or even smell and vibration. Wide data comes from an increasing range of internal and external data sources, such as data marketplaces and exchanges, brokers/aggregators, industry consortia, open data, social media, IoT sensors and digital twins.

### Sample Vendors

Diveplane; Google; iOmniscient; Landing AI; MOSTLY AI; MyDataModels; Owkin; Veritone

### Gartner Recommended Reading

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

Tech Providers 2025: Why Small Data Is the Future of AI

3 Types of Machine Learning for the Enterprise

Understanding When Graph Technologies Are Best for Your Business Use Case

Working With Semistructured and Unstructured Datasets

## Differential Privacy

**Analysis By:** Van Baker, Bart Willemsen

**Benefit Rating:** High

**Market Penetration:** 1% to 5% of target audience

**Maturity:** Emerging

### Definition

Differential privacy is a system for using or sharing a dataset while withholding or distorting certain information elements about individual records in the dataset. The system uses exact mathematical algorithms that randomly insert noise into the data, add parameters for distinguishability, closeness and diversity of outcomes. As such, it ensures that the resulting analysis of the data information-wise does not significantly change without disclosing identifiable information.

### Why This Is Important

Concerns about privacy and the use of personal information in algorithms to serve content or personalize recommendations are growing. As regulatory measures are employed to prevent unauthorized use of this information continue to increase, businesses are looking for ways to protect personally identifiable information while still using the data. One of the technologies that can be deployed to accomplish this is differential privacy.

### Business Impact

Business data holds value and much of it is personal data. Regulations that constrain use of personal data are increasing, and the liability for misusing personal data can be substantial. Businesses need to ensure that their reputation reflects a company that protects customer data. There are many techniques addressing problems in preserving privacy when training AI models. Differential privacy ensures the privacy of individual rows of data while supporting meaningful analysis of aggregate data.

### Drivers

There are a number of market and regulatory factors that are driving the need for differential privacy:

- The need to uncover value from data without crossing the boundaries of ethical or regulatory restrictions on the usage of personal data.
- The goal is not only to reduce risk but to unlock personal data for AI that was previously too difficult to expose.
- It is increasingly likely that more restrictive regulations will be enacted such as the recent European Union regulations centered on the use of algorithms that use personally identifiable information.
- There is increasing risk from sophisticated, state-sponsored bad actors that increasingly target theft of personal information to facilitate fraudulent actions.
- The ongoing pressure to improve business performance by the use of personal data in artificial intelligence and machine learning models.
- The reputation of the business and the trust associated can be significantly damaged by information breach or misuse.
- Exposure is not limited to datasets in control of the business as malicious actors can increasingly combine data sources to reidentify individuals even if the data used by the business is anonymized.
- With differential privacy, source data is not altered as the answer to each query is treated “on the fly.”
- Information value can be maintained in a controllable manner via a privacy budget, delivering the desired level of anonymity and maintaining information value.

### Obstacles

There are a number of obstacles that are causing confusion surrounding differential privacy solutions.

- Available solutions in the vendor landscape that reference the use of technologies to protect privacy are not always comparable.
- Privacy protection solutions use a variety of techniques and they vary in effectiveness.
- Most solutions cover the perspective of anonymity focusing on the extent to which reidentification can occur. Other solutions add measures focused on diversity and closeness to add additional protections from reidentification protection. This can cause confusion when considering solutions to this problem.
- Lack of familiarity with the technique and skilled staff to effectively deploy and manage it, hinders adoption and adequate protection.

### User Recommendations

- When risk is elevated, explore the use of differential privacy techniques to decrease the likelihood of sensitive data exposure.
- Use a privacy impact or data protection impact assessment to establish whether additional means are necessary and relevant to the use case.
- When operating in high-performance environments that require a high-level of precision in analytics models, SRM leaders should compare differential privacy with other privacy-enhancing computation techniques.
- Differential privacy techniques should be a high priority for highly regulated industries such as financial services and healthcare.
- Consider differential privacy techniques when using data across regions where privacy regulations may vary.

### Sample Vendors

Immuta; LeapYear; LiveRamp; PHEMI Systems; Privitar; Sarus Technologies

### Gartner Recommended Reading

Predicts 2021: Balance Privacy Opportunity and Risk

[Top Strategic Technology Trends for 2021: Privacy-Enhancing Computation]

[Preserve Privacy When Initiating Your IoT Strategy]

### Federated Machine Learning

**Analysis By:** Svetlana Sicular, Alexander Linden, Saniye Alaybeyi, Pieter den Hamer

**Benefit Rating:** High

**Market Penetration:** Less than 1% of target audience

**Maturity:** Emerging

#### Definition

Federated machine learning aims at training a machine learning (ML) algorithm on multiple local datasets contained in local nodes without exchanging data samples. Federated ML enables more-personalized experiences without compromising privacy. Local learning may occur in smartphones, softbots, (semi)autonomous vehicles or IoT edge devices.

#### Why This Is Important

Federated ML highlights an important innovation in (re)training ML algorithms in a decentralized environment without disclosing sensitive business information. The adoption of federated ML accelerated over the past year, especially because it has been successfully used in healthcare during the pandemic. Federated ML helps to protect privacy, enables ML and specifically DNNs to use more data, resolves data transfer bottlenecks, and empowers collaborative learning for better accuracy.

#### Business Impact

Federated ML enables collaborative ML by sharing local model improvements at a central level, while keeping the data locally. It especially benefits the IoT, cybersecurity, privacy, data monetization and data sharing in regulated industries. For example, the U.S. National Institute of Health recently reported an average improvement of 16%, and a 38% increase in generalization over local models, as a collaboration result of 20 institutes.

Drivers

- There is a growing need to protect the privacy of local data due to the proliferation of privacy regulations.
- With the increasing hype around edge AI, the data becomes distributed across multiple, heterogeneous edge devices and clouds. Gartner research shows that 76% of organizations are multicloud. Federated ML allows organizations to keep the data in place.
- Data volumes are still growing rapidly, making it more challenging to collect and store big data centrally. This is especially pronounced in the IoT scenarios, where sensor data is collected on the devices and often there is no time or reason to pass it centrally. Due to scalability issues, excessive power consumption, connectivity and latency, we see a move toward edge infrastructure in the form of federated computing architectures.
- The collaborative and parallel solving of complex problems is especially impactful in engineering. The IEEE issued IEEE 3652.1-2020 - IEEE Guide for Architectural Framework and Application of Federated Machine Learning to facilitate solving such problems with a blueprint for data usage and model building across organizations and devices, while meeting applicable privacy, security and regulatory requirements.
- The adaptability of ML to local context and conditions (for example, when necessary to keep the customer data private on their personal devices).
- The prevention of data sharing between competing actors.
- Swarm (federated) learning is emerging as a promising approach in decentralized ML, uniting edge computing, peer-to-peer networking and coordination, enabled by blockchain.

### Obstacles

- System and data heterogeneity requires a lot of coordination and standardization among systems to be fully functional.
- Enabling federated learning requires a complete end-to-end infrastructure stack that integrates capabilities across DataOps, ModelOps, deployment and continuous tracking/retraining, necessitating a high degree of implementation maturity.
- Creating a new, more accurate and unbiased central model from local model improvements can be nontrivial, as the diversity or overlap between local learners and their data may be hard to assess and may vary greatly.
- Federated learning is still not widely known in the enterprise, as it lacks “marketing” on the vendor and researcher sides.
- Security and privacy validation concerns require additional steps.

### User Recommendations

- Apply federated ML to create and maintain decentral smart services or products, while protecting the privacy of users and preventing the need to centrally collect massive amounts of data.
- Give a head start to decentral ML applications by deploying a common, centrally pretrained model while still providing personalization and contextualization by locally retraining the model based on local data and feedback.
- Enable continuous improvement of decentral ML applications with collaborative learning by repeatedly collecting local model improvements to create a new, improved central model and then redeploying it for decentral usage and fine-tuning.
- Keep in mind that many use cases today do not require federated ML. No major platform vendor has a federated ML offering for end users.
- Keep a central reference model to ensure “cognitive cohesion” across distributed models — that is, by avoiding decentralized models to veer off too far from its original purpose.

### Sample Vendors

AI.Reverie; Alibaba; Duality Technologies; Ederlabs; F-Secure; FedAI Ecosystem; Google; Hewlett Packard Enterprise; Intel; NVIDIA; Owkin; Tencent

### Gartner Recommended Reading

Market Guide for Machine Learning Compute Infrastructures

Deploying IoT Analytics, From Edge to Enterprise

Raise Your Product Innovation Quotient With Edge AI

Use Edge AI to Drive Revenue Growth, Forecasting, Customer Engagement and Workforce Planning

## 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

## Chief Data Scientist

**Analysis By:** Carlie Idoine, Farhan Choudhary, Erick Brethenoux

**Benefit Rating:** High

**Market Penetration:** 5% to 20% of target audience

**Maturity:** Adolescent

### Definition

Chief data scientist is an emerging, leadership role responsible for translating data and analytics strategy into efficient and effective implementations of advanced D&A products and services. The role is typically the most senior data science position within an organization and has a specific focus on applied data science approaches.

### Why This Is Important

The complexity, pervasiveness and criticality of advanced analytics and AI require dedicated attention to coordinate use and support of data science, ML and AI for businesses' top priorities. Chief data scientists are responsible for enterprise data science teams and for execution of the D&A vision. They must think tactically, assess the current situation and deliver value today while planning strategically, in parallel, to coordinate and maximize the future use of advanced analytics.

### Business Impact

The business value derived from AI done right is substantially more than what can be accomplished by other means. Chief data scientists are key for unlocking this value. They propel the use of advanced analytics forward by:

- Translating business vision to data and advanced analytics priorities
- Coordinating all advanced analytics initiatives across the organization, minimizing silos while maximizing adoption
- Delivering measurable results and value to the organization

Drivers

- Organizations lacking the ability to understand and communicate the value of advanced analytics, ML and AI initiatives are making efforts to manage and coordinate both centralized and decentralized teams to deliver measurable business outcomes.
- Organizations are digitizing and automating more of their processes with AI and analytics at the core. As AI becomes a critical function in processes underlying digital businesses, it requires leadership skills and oversight.
- Siloed, unstructured approaches to advanced analytics and AI not only consume significant time and resources but also increase the risk and minimize return on investment and overall trust in these techniques. The role of chief data scientist aids breaking down and eliminating silos.
- There is increased commitment to driving advanced analytics throughout the organization but the aim is to do so using a consistent and managed approach. Also, organizations face huge analytical and AI debt as projects grow and become more complicated. A chief data scientist leads the charge of ensuring an efficient path to agile delivery of D&A initiatives.
- The democratization of data science boosting the adoption of ML techniques has generated an increasing amount of ML models that are often not operationalized. The need for better coordination with the lines of business and IT, and the harmonization of DSML practices, require a chief data scientist role.
- The proliferation of “shadow IT” practices across organizations is often the source of MLOps inefficiencies and the inefficient use of data science talents. Chief data scientists have a unique opportunity to federate those talents, physically or virtually.

### Obstacles

- D&A leaders and their IT and business partners often lack effective influence, organization, process and practice to deliver, operationalize and scale DSML solutions and approaches.
- The chief data scientist role may not have enough organizational clout and defined authority to drive the enterprisewide changes required to reap the benefits of AI.
- The lack of business recognition often leaves the organization open to data science poaching, weakening the role of the chief data scientist.
- Recruiting and retaining an experienced chief data scientist, with the right blend of management, technical, business and communication skills, is challenging.

### User Recommendations

- Define the chief data scientist role as a complement to other CxO roles, recognizing that alignment between these roles is critical.
- Work both within (the internal IT team and the broader organization) as well as outside the organization to orient the chief data scientist within the broader community and identify opportunities for learning and partnership.
- Empower chief data scientists to build a diverse team, develop processes and procure tools to deliver models in a way that builds trust while tracking the impact on key business priorities and value generated.
- Leverage the chief data scientist role to drive and coordinate application and exploration of advanced analytics methods and techniques to align those methods with real, prioritized business problems.

### Gartner Recommended Reading

The Chief Data Scientist Role Is Key to Evolving Advanced Analytics and AI

The Current State of Demand for the Chief Data Scientist Role: Q1 2021 Report

## Synthetic Data

**Analysis By:** Anthony Mullen, Alexander Linden

**Benefit Rating:** High

**Market Penetration:** 1% to 5% of target audience

**Maturity:** Emerging

### Definition

Synthetic data is a class of data that is artificially generated, i.e., not obtained from direct observations of the real world. Data can be generated using different methods such as statistically rigorous sampling from real data, semantic approaches, generative adversarial networks or by creating simulation scenarios where models and processes interact to create completely new datasets of events.

### Why This Is Important

One of the major problems with AI development today is the burden in obtaining real-world data and labeling it so AI models can be trained effectively. This is remedied by synthetic data. Furthermore, synthetic data is critical in removing personally identifiable information (PII).

### Business Impact

Adoption is increasing across various industries, along with use in natural language processing (NLP) applications. We predict massive increase in adoption as synthetic data:

- Avoids using PII when training machine learning (ML) models via synthetic variations of original data or synthetic replacement of parts of data.
- Reduces cost and saves time in ML development as it is cheaper and faster to obtain.
- Improves ML performance as more training data leads to better training outcomes.

### Drivers

- In healthcare and finance, buyers' interest is growing as synthetic data can be used to preserve privacy in AI training data.
- To meet increasing demand for synthetic data for natural language automation training, especially chatbots and speech applications, new and existing vendors are bringing offerings to market. This is expanding the vendor landscape and driving synthetic data adoption.
- Synthetic data applications have expanded beyond automotive and computer vision use cases to include data monetization, external analytics support, platform evaluation and the development of test data.
- Increasing adoption of simulation techniques is accelerating synthetic data.
- While row/record, image/video, text and speech applications are common, R&D labs are expanding the concept of synthetic data to graphs. Synthetically generated graphs will resemble but not overlap the original. As organizations begin to use graph technology more, we expect this method to mature and drive adoption.

### Obstacles

- Synthetic data still has significant flaws. It can have bias problems, miss natural anomalies, be complicated to develop or may not contribute any new information to existing, real-world data.
- Data quality is tied to the model that develops the data.
- Buyers are still confused over when and how to use the technology with other data pipeline tools. As the number of techniques in data and model pipeline increases, buyers struggle to determine what techniques to use to achieve their aims (e.g., synthetic data, federated learning, differential privacy) and how to use them together.
- Synthetic data can still reveal a lot of sensitive details about an organization so security is a concern. An ML model could be reverse-engineered via active learning. With active learning, a learning algorithm can interactively query a user (or other information sources) to label new data points with the desired outputs, meaning learning algorithms can actively query the user/teacher for labels.

#### User Recommendations

- Identify areas in your organization where data is missing, incomplete or expensive to obtain, and thus, currently blocking AI initiatives. In regulated industries, such as pharma or finance, exercise caution and adhere to rules.
- Use synthetic variations of the original data or synthetic replacement of parts of data, when personal data is required but data privacy is a requirement.
- Begin with a sampling approach and leverage data scientists to ensure statistical validity of the sample and distribution of the synthetic data.
- Leverage specialist vendors while the technology matures.
- Mature toward the simulation-driven approach, emphasizing creating agents and processes within a simulation framework to generate permutations of interactions that result in synthetic data.

#### Sample Vendors

AI.Reverie; Bitext; MOSTLY AI; Neuromation; Tonic; Twenty Billion Neurons (TwentyBN)

#### Gartner Recommended Reading

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

2021 Strategic Roadmap for Enterprise AI: Natural Language Architecture

Cool Vendors in AI Core Technologies

### Transfer Learning

**Analysis By:** Anthony Mullen, Saniye Alaybeyi

**Benefit Rating:** High

**Market Penetration:** 1% to 5% of target audience

**Maturity:** Adolescent

### Definition

Transfer learning is the reuse of previously trained machine learning models as an advanced starting point for new purposes, in order to reduce the learning time and data requirements required to attain acceptable performance.

### Why This Is Important

Transfer learning is attractive as it enables rapid training, reduces the amount of data needed and improves predictive performance in comparison to models trained from scratch. A start point is a repository of models and these models can be sourced from internal efforts (custom models trained on internal data) or external sources. Transfer learning also advances the broader field of AI as it allows AI to generalize — use what is learned in one task to more quickly learn another, related task.

### Business Impact

- Transfer learning will impact all use of ML, both in terms of how organizations apply it, and the technology they acquire with the capability embedded. The shift to nonsymbolic and hybrid NLP techniques, combined with transfer learning, enables the extraction of richer insights from text-based content.
- Transfer learning promises the possibility to attain acceptable performance with less training data.
- Transfer learning will support progressive automation in adjacent information-rich domains.

#### Drivers

- Increased application in language automation: The use of transformer models like BERT and GPT3 as a starting point for natural language model development has seen accelerated adoption into vendor model pipelines (e.g., transformer base model > domain model > client model).
- Increase in model marketplaces: The availability of industry-specific repositories allows developers to find and reuse neural network models, e.g., BoozAllen, OpenNN and industry specialists like Kipoi (genomics).
- Applicability to multiple use cases and verticals: We see transfer learning being used across a number of model types (computer vision, language, predictive) in multiple domains such as healthcare, gaming, autonomous driving and digital commerce.
- Delivery of pretrained "minimum viable" models by vendors to their clients, who can apply TL to tailor the ML model to their specific needs. In application areas such as computer vision, or other areas, like pretrained models for predictive maintenance, models are delivered with an asset, which can then be further contextualized to the specific operating conditions.

#### Obstacles

- Not yet a turnkey experience: Transfer learning today is a capability embedded into existing platforms or a method applied by system integrators and analytics consultancies. It is not yet a product in the same way that AutoML is. Buyers are looking for a productized approach here, which would accelerate adoption.
- Sufficient well-documented models available: Documentation on source model development promotes trust, the tools to reuse the data are in place, and there is enough subsequent retraining on new data to attain successful use. As the AI field becomes more regulated, the lineage of models used in transfer learning becomes more important.

### User Recommendations

- Maintain internal directories of AI models and datasets: Work with your data and analytics leaders to utilize metadata management initiatives to identify internal datasets. AI centers of excellence (COEs) or similar should facilitate.
- Explore both internally and externally for models that can be used: Those with a more mature level of AI adoption should additionally ask how their current models might be reused in related domains and similar tasks.
- Check the tools you use to create and train models to determine their support for transfer learning, which should also be a requirement for any new tools. A mandate for transfer learning can help to organize approaches to AI into a hierarchy.
- Loop in CSOs to educate them about the approach of using transfer learning to develop your initial position on AI risk. For example, the progeny of the original data for the base model and security risks of open base models you may use.

### Gartner Recommended Reading

2021 Strategic Roadmap for Enterprise AI: Natural Language Architecture

Critical Capabilities for Data Science and Machine Learning Platforms

3 Types of Machine Learning for the Enterprise

Data Science and Machine Learning Trends You Can't Ignore

## 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 Science Education

**Analysis By:** Peter Krensky, Farhan Choudhary

**Benefit Rating:** High

**Market Penetration:** 5% to 20% of target audience

**Maturity:** Adolescent

### Definition

Higher education institutions and solutions vendors offer learning experiences for credit-bearing courses and independent study of data science capabilities. These include Massive Open Online Courses (MOOCs), diplomas, undergraduate and postgraduate degrees.

### Why This Is Important

Even as talent becomes more available and less prohibitively priced, many organizations and forward-thinking professionals are exploring avenues for upskilling in data science and machine learning (DSML). At the same time, there are numerous and varied tools designed for users with minimal DSML experience and newly acquired skills. Education is the best answer to further narrow the data science talent gap and prepare organizations for optimal adoption of next-generation AI and ML technologies.

### Business Impact

Data science education helps leaders take individuals with business or technical experience and domain expertise and equip them to become citizen data scientists. Education is also becoming vital to preparing the large populations of augmented consumers to better engage with and understand embedded machine learning. Continuing education is also a vital practice to develop and retain expert data scientists.

### Drivers

Data science class sizes, faculties and degree programs have been expanding in traditional universities for the past decade. General upskilling and online education in data science are thriving, and online education activity has only intensified over the last year.

Key drivers of data science education at all levels include:

- Abundant and lucrative job opportunities for those with data science skills and ML literacy
- New and expanded university degree programs and curriculums in analytics and data science
- Large populations of knowledge workers interested in upskilling in DSML
- Training and certification programs of all kinds from software vendors, some tied to specific technologies

- Low technical barrier to entry in DSML with the advent of low-code/no-code platforms and augmented DSML, making the area well within reach of interested individuals
- DSML talent development as a retention strategy
- Rapid progress of research and new technologies coming out of academia and corporate research labs
- The low cost of a foundational data science education (under $1,000 for strong independent learners)

Obstacles

- There are an overwhelming number of online course options designed for different personas and experience levels.
- There are many popular and excellent options, but there is also plenty of content that delivers minimal impact or fails to justify its cost. Formal programs and graduate degrees bring additional concerns around high costs.
- Students and organizations recognize that data science is a moving target, and certain areas of study can quickly fall out of favor or even become obsolete.
- The DSML space is evolving very quickly with rapidly changing standards and desired skills.

Other common obstacles in data science education initiatives include:

- Training people out the door (i.e., sponsoring the development of skills that attract recruiters and lead to the departure of valued employees)
- No expert mentorship available for citizen data scientists after completing foundational education
- Experts lacking education and experience in business considerations around data science use cases and practical applications
- Underestimating DSML complexity and oversimplifying it to foundational elements

### User Recommendations

- Evaluate the current university program landscape in data science and build an educational profile for the various roles in your data science team.
- Build and expand relationships with local universities to establish internship programs and a data science talent pipeline into your organization.
- Sponsor all MOOCs under $1,000 in total cost with the expectation that the majority of classroom work will be done outside of working hours.
- Offer proven upskillers company time dedicated to unstructured learning and professional development.
- Expect leadership from expert data scientists on key new topics, leading tools and technologies, and how to manage common pitfalls that less experienced practitioners will encounter.
- Accept that the majority of learning and skill development is done after classroom learning in the course of experimentation and project delivery.
- Provide educational resources and training on human skills such as presentation skills, relationship building, translation of technical information and leadership.

### Gartner Recommended Reading

How to Approach Online Courses in Data Science and Machine Learning

Tool: Data Science and Machine Learning Education — Navigating the University and MOOC Landscape

Tool: Data Science and Machine Learning Education — Navigating the Vendor Training Landscape

How to Design an Effective Data and Analytics Training Program to Improve Data Literacy

## 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

### X Analytics

**Analysis By:** Rita Sallam, Michael Woodbridge

**Benefit Rating:** High

**Market Penetration:** 1% to 5% of target audience

**Maturity:** Emerging

#### Definition

X analytics is an umbrella term where “X” stands for a range of structured and unstructured content. It represents the type of analytics done on one or more types of content, including text, video, image, voice, vibration, emotion, etc., to support innovation and augment decision making.

#### Why This Is Important

- Combining content types via X analytics has the potential to create a richer situational awareness and uncover new insights beyond those that can be derived from only highly structured/transactional data.
- As organizations face unprecedented disruption and uncertainty and must accelerate their response to change, there is an opportunity to leverage previously untapped and unique data sources and combinations to transform processes, activities and decisions.

### Business Impact

- Most global enterprises across domains and industries will experiment or accelerate use of X analytics to reduce cost and risk, and drive growth and innovation.
- Examples include using X analytics for everything from predictive maintenance and supply chain optimization to predictive agriculture, addressing climate change, and disease prevention.
- In sales, X analytics is being used to analyze audio and video streams for deal insights, competitive intelligence and pricing recommendations.

Drivers

- Organizations have massive amounts of unused content that has untapped potential.
- By 2025, AI for video, audio, vibration, text, emotion and other content analytics will trigger major innovations and transformations in 75% of Fortune 500 global enterprises.
- X analytics has the potential to move organizations beyond storing and managing content, which has been done for years, to extract meaningful insights from these sources. This has been difficult until now.
- The maturity of AI tools and techniques for analyzing content including video, audio, emotion and text will spur broader adoption and enable a new wave of data-based innovation.
- Cloud-based AI services for a broad range of content from algorithm marketplaces are making content analytics more accessible as well as scalable to mainstream organizations.
- Data marketplaces and exchanges are making larger and more pretrained datasets more widely available. Approaches, including synthetic data and techniques, and augmentation techniques are also maturing.
- Advances in and adoption of deep-learning-based video and image analysis techniques and products have been catalysts for broader adoption. Text analytics has also seen dramatic advances through deep learning techniques through the advent of transformer models (via BERT and GPT techniques). This has been underpinned by the improved price/performance of computer processing power, especially from the cloud.
- More analytics vendors are adding X analytics capabilities as part of their analytics applications and platforms.
- Organizations are aggressively thinking about how to use new kinds of data and analysis. COVID-19 has accelerated the need to use wider (more types of data) rather than deeper (more historical data) across a broad range of use cases, like supply chain optimization, drug discovery and patient diagnosis, among many others.

### Obstacles

- While different forms of content analytics (particularly text analytics) have been deployed for many years, adoption has been limited due to a lack of skills and specialized tools. Many organizations still avoid leveraging content due to the perceived difficulty and need for new skills.
- The difficulty of combining various techniques used to handle specific types of datasets — like deep learning for videos, symbolic algorithms for text analytics, knowledge graphs, etc. — is a challenge.
- Data sourcing, data quality, bias and privacy protection are common challenges that can be cost prohibitive for large datasets. Finding the right data for specific use cases can be difficult and expensive and require governance.
- The market for tools to analyze the range of content is fragmented and will likely require use of multiple vendors.
- Organizations are often uncertain about the business value of insights by using X analytics.

### User Recommendations

- Identify low-hanging fruit as well as innovation opportunities that align to business priorities that could leverage X analytics for richer situation awareness and decision making. Leverage use-case examples, case studies and conduct proofs of concept (POCs) to demonstrate value, and to understand the data, technical and organizational gaps that need to be filled for success.
- Revise your data collection, management and integration practices to successfully take advantage of X analytics.
- Revisit or complement content as sources of latent analytical value, especially when combined with structured data.
- Explore X analytics capabilities and roadmaps from your existing vendors. This includes insight engines for text and cloud vendors for image, video and voice analytics. Consider small disruptive startups and cloud providers as sources for innovation.
- Assess the necessary compute and storage resources needed to train and run effective AI and ML models that leverage content.

### Gartner Recommended Reading

Magic Quadrant for Insight Engines

Top Trends in Data and Analytics for 2021

Emerging Technologies: Tech Innovators for Computer Vision

Emerging Technologies: Emergence Cycle of Video Analytics

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

## 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

#### 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

### MLOps

**Analysis By:** Farhan Choudhary, Jim Hare, Pieter den Hamer, Erick Brethenoux

**Benefit Rating:** High

**Market Penetration:** 5% to 20% of target audience

**Maturity:** Emerging

#### Definition

Machine learning operationalization (MLOps) aims at streamlining the deployment, operationalization and instantiation of ML models. It supports the release, activation, monitoring, performance tracking, management, reuse, update, maintenance, risk and compliance management, and governance of ML models.

#### Why This Is Important

Operationalization of machine learning projects is often an afterthought, which keeps organizations from realizing the true value of their investments. MLOps aims to standardize the deployment and management of ML models by supporting the release, activation, monitoring, performance tracking, management, reuse, maintenance, risk and compliance management, and governance of ML artifacts.

### Business Impact

- Integration — Integrate advanced analytics and ML platforms to provide a unified ML operationalization pipeline.
- Catalog — To store and secure data, analytical and ML artifacts for ease of collaboration and reusability.
- Governance — To ensure auditability and adherence to all internal and external security policies, procedures and address potential privacy issues.
- Coherence — To provide functional bridges between the development and operationalization cycles.

### Drivers

- Organizations face machine learning model debt in many cases, which keeps them from realizing the true value of their investments. MLOps helps pave a clear path to help organizations move from experimentation to production.
- Organizations want to ensure the integrity (technical and business), transparency and sustainability of deployed ML models by establishing a systematic operationalization process for their machine learning projects that differs from traditional software engineering projects.
- Organizations want to maximize their operationalization success by securing the help of domain experts, process engineers, IT professionals and business practitioners, in addition to existing data science talent. MLOps brings all these personas together.
- Organizations seek to minimize complex maintenance procedures of deployed machine learning models by monitoring and revalidating their business value on an ongoing basis.

### Obstacles

- Organizations tend to think of MLOps just as a technology or procedure; instead, it is a way of working that involves different personas coming together to productionize an ML workflow.
- MLOps tools and platforms today primarily focus on the management, monitoring and governance of machine learning models and, in most cases, do not assist in the end-to-end development, deployment, management and governance of machine learning pipelines.
- Most organizations focus on the data science and machine learning algorithm and model development, and overlook the aspect of operationalization.
- Machine learning is the most leveraged AI technique, but it's not the only one. There's a gap when mature organizations tend to operationalize other AI models.
- The vendor landscape for MLOps is rapidly evolving, which creates confusion for organizations looking for the most efficient way to operationalize their machine learning workflows.

### User Recommendations

- Establish a systematic MLOps process through Gartner's MLOps framework.
- Ensure the business value of ML deployments while prioritizing use cases by establishing close, ongoing dialogue with, and explicit buy-in from, business counterparts. The earlier the dialogue happens, the more successful the model operationalization will be.
- Organize for MLOps by placing them within the DS lab, IT or lines of business (LOBs) depending upon the expected business outcomes, the size of the ML project team and the complexity of the initiatives.
- Define roles and responsibilities of data scientists, IT and MLOps by aligning team members with stages in the DS and ML life cycle.

### Sample Vendors

Amazon Web Services; Databricks; Dataiku; DataRobot; Datatron; IBM; Iguazio; Microsoft

### Gartner Recommended Reading

Use Gartner's 3-Stage MLOps Framework to Successfully Operationalize Machine Learning Projects

Use 3 MLOps Organizational Practices to Successfully Deliver Machine Learning Results

Understanding MLOps to Operationalize Machine Learning Projects

## Deep Learning

**Analysis By:** Farhan Choudhary, Alexander Linden, Svetlana Sicular

**Benefit Rating:** Transformational

**Market Penetration:** 5% to 20% of target audience

**Maturity:** Adolescent

### Definition

Deep learning (DL) is a variant of machine learning algorithms that uses multiple layers to solve problems through extraction of knowledge from raw data, and transforming it at every level. These layers incrementally obtain higher-level features from the raw data, allowing the solution of complex problems with higher accuracy, less features and less manual tuning.

### Why This Is Important

Deep learning can certainly outperform traditional machine learning or shallow learning techniques while working with complex and often high-dimensional data, such as images, speech and text. With sufficient training and inference, DL reduces the need for tedious feature engineering, and can generate superior results with complex quality data (especially in cases of fraud detection, quality analysis and demand prediction).

### Business Impact

Deep learning allows organizations to generate insights from disparate, especially unstructured, and, at times, limited data, from disparate data sources. All this success is rooted in the ability of DL algorithms to exploit weak signals in the dataset, which in isolation may not carry any meaning, but in a group may highlight results that would have been neglected or not even surfaced.

### Drivers

- DL applicability has been most successful in the domains of vision, speech and text, across industries such as healthcare, transportation, national security, military, criminal justice, cities, finance and social media.
- Methods such as reinforcement learning, transfer learning, deep belief networks, evolutionary learning algorithms are propelling the use of deep learning in certain domains.
- Organizations looking to enrich their decision-making process by leveraging wide unstructured data such as image, audio, video or text, can leverage DL techniques.
- Availability of off-the-shelf solutions and dedicated hardware is also driving the adoption of deep learning.
- Recent advancements in NLP techniques leveraging DL methods have propelled the advancement and use of transformers, which promise state-of-the-art results in conversational platforms.

### Obstacles

- The infrastructure investments required to create and maintain deep learning solutions are high.
- DL methods are construed as black box in nature, so governing and ensuring explainability of these solutions is challenging.
- DL solutions rely on the availability of high volumes of quality and correctly labelled data, which is seldom available with an average client.
- DL in visual recognition tasks rely on extracting information from pixel-based features, which could lead to undesirable or suboptimal results.
- The skills required to create and manage DL solutions from scratch is hard to get by.
- There is limited support and capabilities around security, privacy and governance for vendors providing DL capabilities as a service, which adds a layer of complexity over already black-box implementations.

### User Recommendations

- Explore deep learning techniques when shallow learning techniques have failed to generalize a learning model.
- Examine and select business areas, where deep learning can provide best value, especially where there is wide and heterogeneous data.
- Create a diverse talent pool from industry and academia that can ensure interpretability as well as privacy, compliance, ethics and governance in DL solutions.
- Examine prepackaged solutions first and then move on to custom-made solutions for the business using deep learning.
- Explore adversarial learning techniques to enhance the applicability of deep learning approaches.

### Sample Vendors

Facebook; Google; Landing AI; Microsoft; NNAISENSE; NVIDIA

### Gartner Recommended Reading

Innovation Tech Insight for Deep Learning

Introducing Deep Learning Abstraction Methods

3 Types of Machine Learning for the Enterprise

## Sliding into the Trough

### Augmented DSML

**Analysis By:** Carlie Idoine, Farhan Choudhary

**Benefit Rating:** Transformational

**Market Penetration:** 5% to 20% of target audience

**Maturity:** Adolescent

#### Definition

Augmented data science and machine learning (augmented DSML) uses artificial intelligence to help automate and assist, in variable degrees, key aspects of a data science and machine learning process. These aspects include data access and preparation, feature engineering and model selection, as well as model operationalization, model explanation, model tuning and management.

#### Why This Is Important

Augmented DSML, a subcategory under the augmented analytics umbrella, reduces the requirement for specialized skills to generate and operationalize advanced analytical models. It enables citizen data scientists to create, manage and embed ML models into business applications. Highly skilled data scientists can use augmented DSML to increase productivity by automating time-consuming, labor-intensive and mundane, simple steps, while reducing error or bias inherent in manually developed models.

#### Business Impact

Augmented DSML learning fosters:

- Data-driven decision making by democratizing access to advanced analytics.
- Reduced time required to build and deploy models, while offering more flexibility and increased business responsiveness.
- Reduced reliance on scarce data science experts, while enabling those with business domain knowledge to practically use DSML.
- Organic growth and expansion of analytics portfolios by enabling access and collaboration among various personas, which fosters trust and acceptance.

### Drivers

- Increasingly decentralized business users have a need for more advanced analytics that incorporate analytics in ad hoc decision making and embed analysis directly within their business processes and systems.
- Shortages of expert data science skills and high costs to secure and retain data science talent are driving new approaches to enable use of advanced analytics without traditional experts.
- Specific steps in the ML pipeline are time-consuming and mundane (e.g., data preparation, feature engineering, model optimization), and so are ripe for automation.
- Increased need for collaboration between those possessing knowledge of advanced analytical techniques and those with strong business acumen and organizational experience.
- Augmented capabilities are increasingly included by vendors across the complete analytics process within all DSML platforms.

### Obstacles

- Expert data scientists often underestimate the net business value provided by augmentation that enables nonexperts or themselves to be more productive.
- Business-user-led analysis often surfaces issues in how data is collected, organized and managed. D&A leaders must be prepared for new utilization of data.
- Lack of collaboration processes and tools between citizen data scientists and with data scientists.
- Upskilling in advanced analytics techniques as well as providing augmented DSML tools are necessary to fully use augmented DSML approaches. In addition, learning how to apply these to real, prioritized business problems will take time and guidance from experienced data scientists.
- Expectations for a fully automated approach often are not met, except in narrow use cases and limited scenarios.

### User Recommendations

- Use augmented DSML to extend, but not replace, traditional DSML approaches.

- Recruit/upskill and enable citizen data scientists to increase accessibility and grow use of augmented DSML. In addition, support the use of augmented DSML to increase efficiency and mitigate bias of models.
- Extend and integrate with the existing analytics and DSML technology stack when possible. Prioritize vendor solutions that include augmented capabilities.
- Manage and guide your augmented DSML approach, with significant focus on governance and explainability, data access and data quality. Leverage collaboration between experts and nonexperts to validate and audit the models and approach.
- Incorporate collaboration tools and processes to enable citizen and expert data scientists, business analysts and application developers to work together to define, build and manage models.
- Create a long-term strategy for augmented DSML in the cloud.

### Sample Vendors

Aible; Alteryx; BigSquid AI; dotData; DataRobot; H2O.ai; IBM; RapidMiner; SAS; 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

How Augmented DSML Makes Data Science Projects More Efficient

Best Practices to Avoid Citizen Data Science Failure

Maximize the Benefits of Augmented Analytics With a Strategic Action Plan

## 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

### Data Labeling and Annotation Services

**Analysis By:** Anthony Mullen

**Benefit Rating:** Moderate

**Market Penetration:** 1% to 5% of target audience

**Maturity:** Adolescent

### Definition

Data labeling and annotation services (DLA) support classification, segmentation, transformation or augmentation procedures to enrich data for artificial intelligence (AI) projects. These services and associated platforms route and allocate tasks to both internal staff and external third-party knowledge workers.

### Why This Is Important

The need for labeled data has dramatically increased in order to remove the bottleneck in developing AI solutions — especially those particular to industry use cases. Given the typical lack of internal skills and systems, DLA services are often the best option (by cost, quality and availability) to provide necessary data for best AI results.

Today, at least, some AI solutions would not be possible without human-based labeling (e.g., car driving, image recognition, search engine tuning).

### Business Impact

Major impacts are:

- Scenarios that do not require deep domain knowledge can accelerate annotation by using external knowledge workers.
- While mostly used in preproduction of models the real-time human-in-the-loop solutions where models are continually trained and calibrated, such as chatbots or recommendation engines, will provide ongoing benefit.
- Business users need to join the human-in-the-loop workflows to route and train handover and moderation tasks to subject matter experts.

### Drivers

We see the following drivers accelerating use of these services:

- Growth of investment in AI requires scaling data pipelines for AI. The broader investment in AI raises demand for these services.

- Growth in language automation offerings. Natural language technology workload outsourcing for speech, conversational AI and document labeling is a major area of growth in this market.
- Semantic support. Not all data that needs labeling is in row, picture or video form. The last 12 months have seen outsourcing of graph labeling and stronger use of semantic assets (e.g., ontologies) to support quicker workflow in labeling.
- Increased diversity of use cases. These services can accelerate and unlock a wealth of use cases across all industries, and core competencies in natural language automation and computer vision. Vendors in the marketplace today have dedicated offerings for commerce, robotics and autonomous vehicles, retail, GiS/maps, AR/VR, agriculture, finance, manufacturing and transportation, and communications.

#### Obstacles

While the supervised learning approach is predominant, DLA services' usage will grow. Obstacles include:

- **Challenger methods**. Data labeling is one of many approaches to get data for models. Few shot learning, transfer learning, synthetic data, semantic platforms and data marketplaces compete for use.
- **Challenges remain around third-party knowledge workers' quality and security** to annotate the data, somewhat ameliorated by the development of reputation systems and prequalification tests.
- **No consolidation of AI-task-outsourcing marketplaces.** The translation ecosystem, the gig economy and data labeling and annotation are as yet not a simplified coherent "language operations" for organisations.
- **Supply outstrips demand and price points are often uneconomical for large-scale data**. Many vendors have entered this space in the last year and demand from buyers does not yet match supply. Pricing and business models vary considerably among providers, and buyers find it difficult to estimate costs.

### User Recommendations

- Design development and production workflows to leverage a mixture of internal and external knowledge workers.
- Ensure the provider you choose has methods to test its pool of knowledge workers for domain expertise and measures around accuracy and quality.
- Model costs to avoid surprises by exploring and estimating the spend across the variety of business models, which range from label volumes and project-based to per annotator/seat costs.
- Allow data scientists to focus their time on more valuable tasks and lighten their load in classifying and annotating data by using these services.
- Use providers with real-time human-in-the-loop solutions for production systems like chatbots and recommenders to handle low-confidence thresholds, spikes in demand or access to real-time knowledge not present in the enterprise.

### Sample Vendors

Alegion; Amazon; Appen; Cloudfactory; Datasaur; Infolks; Lionbridge; Playment; Scale; Yandex

### Gartner Recommended Reading

Strategic Roadmap for AI: Natural Language Architecture

Individuals, Groups and Society in the Loop of Artificial Intelligence Design and Development

Market Guide for AI Translation Services (Bern Elliot)

## 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

### Advanced Image/Video Analytics

**Analysis By:** Nick Ingelbrecht

**Benefit Rating:** Transformational

**Market Penetration:** 5% to 20% of target audience

**Maturity:** Adolescent

#### Definition

Advanced image/video analytics is the application of machine learning methods (including deep neural networks) to automatically identify significant information contained in image and video streams (a series of images or pixels) in the visible and nonvisible light spectrum.

#### Why This Is Important

Advanced image/video analytics comprises a collection of technologies and applications that automatically interpret the world in both visual and nonvisual spectrums. Advanced image/video analytics is transformational across myriad business situations where the most relevant information is visually encoded. Not deploying advanced image/video analytics may imply underperforming or unworkable solutions, absent analysis of visual information.

#### Business Impact

Advanced image/video analytics is applicable to many industries and use cases, including security, automotive, robotics, retail and commercial property, healthcare, manufacturing, supply chain/logistics, banking and finance, agriculture, government, and the media and entertainment industries. Gartner anticipates early mainstream adoption of advanced image/video analytics solutions in the 2023–2025 time frame.

#### Drivers

Advanced image/video analytics has moved further down into the trough as solutions have continued to mature and new applications and use cases have begun to emerge:

- Image/video analytics using deep neural networks and advanced data modeling is gaining traction in security, retail, automotive, manufacturing, healthcare and other specialist vertical markets. By contrast, traditional image/video analytics using geometric analysis and rule-based systems has already reached early mainstream adoption. Advanced video analytics applications include facial recognition in crowds, OCR, license-plate recognition and autonomous vehicles, and in the retail industry, shelf and shopper analysis.

- The market for computer vision tooling and services (e.g., data annotation, augmentation and preparation) is growing fast, which is increasing customer demand for greater levels of automation and evaluation of image/video data.

- Exponential increases in image/video traffic driven by the proliferation of cameras and multispectral sensors are driving demand for automation.

- The application of deep neural networks for advanced image/video analytics has raised the bar in terms of nuisance alarm management and new functionality, especially in human behavior recognition and complex classification tasks.

- Product maturity and improved price/performance will drive mainstream adoption during the 2023 to 2025 time frame. This will be enabled by more embedded edge inferencing in sensors and edge devices, along with more mature cloud services, vertical-specific solutions, packaged applications, and self-configuring, integration-ready third-party applications.

- As the potential of AI using traditional data streams becomes exhausted, attention will increasingly be paid to more complex data streams, such as video and audio.

### Obstacles

Mainstream adoption remains elusive due to:

- A lack of plug-and-play solutions
- Integration and scaling challenges
- The underestimated sparsity of properly labeled data
- Fragmented markets, diverse buying centers and product evaluation challenges
- Proprietary algorithms and patent pools
- Lack of independent standardization and performance benchmarks

- Price, performance and reliability: high-end systems are expensive to maintain and support, and building business cases with adequate ROI remains challenging.

### User Recommendations

- Evaluate the total cost of ownership (TCO) of image/video analytics solutions against alternative vendor architectures and associated costs.
- Leverage image/video analytics to answer both critical issues (e.g., COVID-19 mitigation) and broader business questions (e.g., improving worker safety, enhancing customer experience).
- Hold image/video analytics vendors/integrators accountable for meeting agreed project outcomes rather than the performance of individual system elements.
- Pilot image/video analytics solutions to validate vendor claims, and test solutions in situ in different lighting and environmental conditions.
- Adopt a total systems approach when considering image/video analytics: Balance trade-offs between different elements and resist internal pressures for piecemeal upgrades and bolt-on investments.
- Evaluate the disruptive impact of image/video analytics on existing work practices and implement new cost-optimized workflows and change management measures for maximum business value.

### Sample Vendors

AnotherBrain; Binah.ai; Deepomatic; Herta; iOmniscient; Landing AI; Matroid; Microsoft Azure; Trax; viisights

### Gartner Recommended Reading

Emerging Technologies Tool: Video Analytics Functionality Matrix

Emerging Technologies: Video Analytics Functionality Spectrum, 2021

Emerging Technologies: Top Use Cases in Machine Vision

Emerging Technologies and Trends Impact Radar: 2021

Uncovering Artificial Intelligence Business Opportunities in Over 20 Industries and Business Domains)

Emerging Technologies and Trends Impact Radar: 2021

Emerging Technologies: Tech Innovators for Computer Vision

Emerging Technologies: Top Advanced Computer Vision Use Cases for Retail

Cool Vendors in AI for Computer Vision

Emerging Technologies: Emergence Cycle of Video Analytics

## Climbing the Slope

### 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

### 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

## 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

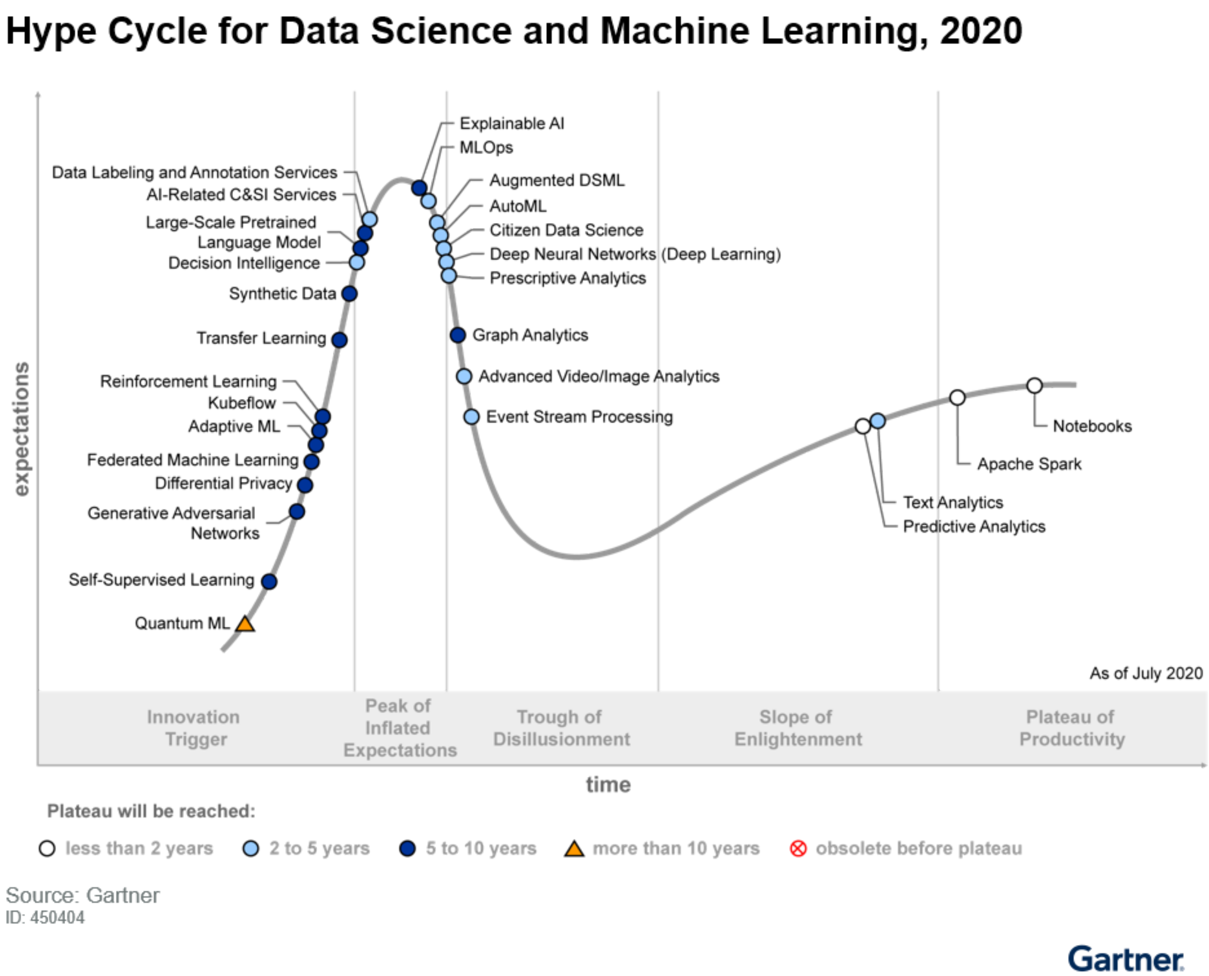
Maximize the Benefits of Augmented Analytics With a Strategic Action Plan

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 Data Science and Machine Learning, 2020




Source: Gartner (July 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 (August 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 (August 2021)

### Table 4: Maturity Levels

(Enlarged table in Appendix)

| *Maturity Levels* | *Status* | *Products/Vendors* |
|---|---|---|
| *Embryonic* | In labs | None |
| *Emerging* | Commercialization by vendors<br>Pilots and deployments by industry leaders | First generation<br>High price<br>Much customization |
| *Adolescent* | Maturing technology capabilities and process understanding<br>Uptake beyond early adopters | Second generation<br>Less customization |
| *Early mainstream* | Proven technology<br>Vendors, technology and adoption rapidly evolving | Third generation<br>More out-of-box methodologies |
| *Mature mainstream* | Robust technology<br>Not much evolution in vendors or technology | Several dominant vendors |
| *Legacy* | Not appropriate for new developments<br>Cost of migration constrains replacement | Maintenance revenue focus |
| *Obsolete* | Rarely used | Used/resale market only |

Source: Gartner (August 2021)

## Evidence

Gartner’s 2019 AI in Organizations Study was conducted online during November and December 2019 among 607 respondents from organizations in the U.S., Germany and the U.K. Quotas were established for company size and for industries to ensure the sample was a good representation across industries and company sizes. Organizations were required to have developed AI or intend to deploy AI within the next three years.

Respondents were screened to be part of the organization’s corporate leadership or report into corporate leadership roles, have a high level of involvement with at least one AI initiative, and have one of the following roles when related to AI in their organizations: determine AI business objectives, measure the value derived from AI initiatives, or manage AI initiative development and implementation.

Results of this study do not represent global findings or the market as a whole, but they reflect sentiment of the respondents and companies surveyed.

## Document Revision History

Hype Cycle for Data Science and Machine Learning, 2020 - 28 July 2020

Hype Cycle for Data Science and Machine Learning, 2019 - 6 August 2019

Hype Cycle for Data Science and Machine Learning, 2018 - 23 July 2018

Hype Cycle for Data Science and Machine Learning, 2017 - 28 July 2017

Hype Cycle for Data Science, 2016 - 25 July 2016

Hype Cycle for Advanced Analytics and Data Science, 2015 - 6 July 2015

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## Recommended by the Authors

Some documents may not be available as part of your current Gartner subscription.

Understanding Gartner's Hype Cycles

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

Data and Analytics Worlds Collide: A Gartner Trend Insight Report

Convergence of Analytics and Business Intelligence, Data Science and AI

Uncovering Artificial Intelligence Business Opportunities in Over 20 Industries and Business Domains

Toolkit: How to Rank and Prioritize Your Use Cases With a Gartner Prism

Understanding Use Case Prisms for Prioritizing Artificial Intelligence Investments

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## Table 1: Priority Matrix for Data Science and Machine Learning, 2020

| Benefit | Years to Mainstream Adoption | | | |
|---|---|---|---|---|
| | Less Than 2 Years | 2 - 5 Years | 5 - 10 Years | More Than 10 Years |
| Transformational | | Advanced Image/Video Analytics<br>Augmented DSML<br>Citizen Data Science<br>Composite AI<br>Decision Intelligence<br>Deep Learning<br>Event Stream Processing | Adaptive ML<br>Composable D&A<br>Generative Adversarial Networks<br>Self-Supervised Learning | Quantum ML |
| High | In-DBMS Analytics<br>Predictive Analytics | Chief Data Scientist<br>MLOps<br>Synthetic Data<br>X Analytics | AI TRiSM<br>Data Science Education<br>Differential Privacy<br>Explainable AI<br>Federated Machine Learning<br>Graph Analytics<br>ModelOps<br>Reinforcement Learning<br>Small and Wide Data<br>Transfer Learning | |
| Moderate | | Data Labeling and Annotation Services<br>Text Analytics | Feature Stores | |

| | | | | |
|---|---|---|---|---|
| Low | | | | |

Source: Gartner (August 2021)

## Table 2: Hype Cycle Phases

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