Democratize Data Science Initiatives With Augmented DSML

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Initiatives: Analytics and Artificial Intelligence for Technical Professionals

Augmented DSML brings in transformational innovation by enhancing productivity and operationalizing Data Science initiatives. Data and analytics technical professionals can use this research to understand the intricacies and learn to complement Augmented DSML within their data science initiatives.

Overview

Key Findings

- Commercial off-the-shelf products now enable more augmented DSML capabilities that benefit business users and citizen data scientists — without requiring advanced skills by leveraging self-service supervised ML to develop prototypes with limited reliance and support from DSML experts.
- Augmented DSML makes data science and ML development more accessible to citizen data science roles like business analysts and developers, while empowering data science experts to be more productive and focused on creative, high-value tasks, rather than model deployments.
- Augmented DSML provides game-changing opportunities, impacting analytics and automation in terms of new business opportunities and data science productivity. However, more work is needed to match the pace of the evolving data science domain before it can become mainstream and for the complete autonomy of human experts.

Recommendations

Data and Analytics Technical professionals responsible for DSML architectures and development must:

- **Select** an augmented DSML solution based on your business use cases, data characteristics, supported data types and the skills of your data science team.
- **Evaluate** capabilities in the augmented DSML solution that can complement your existing DSML processes which are manually intensive, time-consuming, customer-centric and potential trade-offs to the current approach.
- **Extend** traditional DSML processes with augmented DSML deployments (where applicable) to improve productivity, efficiency and collaboration across various aspects of the analytics pipeline — such as data preparation, feature engineering, model selection, validation, training and tuning.
- **Approach** DSML vendor claims with caution regarding processes they can automate. The same applies for black box solutions, where responsible DSML is important. Developing accurate DSML processes, such as operationalization and forecasting requires human knowledge, expert oversight and involvement from the data science community — including citizen data scientists.

Strategic Planning Assumptions

By 2025, a scarcity of data scientists will no longer hinder the adoption of data science and machine learning in organizations.

By 2023, 40% of application development teams will be using augmented DSML in their data science initiatives.

Analysis

Today, data scientists, machine learning experts and business domain users rely on data science and machine learning platforms to manage their models, features, algorithms and workflows that can be complex, iterative, lengthier and inefficient.

Despite the complexity and inefficiencies in building ML applications, recent years have seen a rapid increase in ML applications and a growing desire to streamline and democratize ML capabilities to diverse users. This growing trend has created a demand for automated and augments machine learning in the data science domain.

Here are some of the key takeaways from this research:

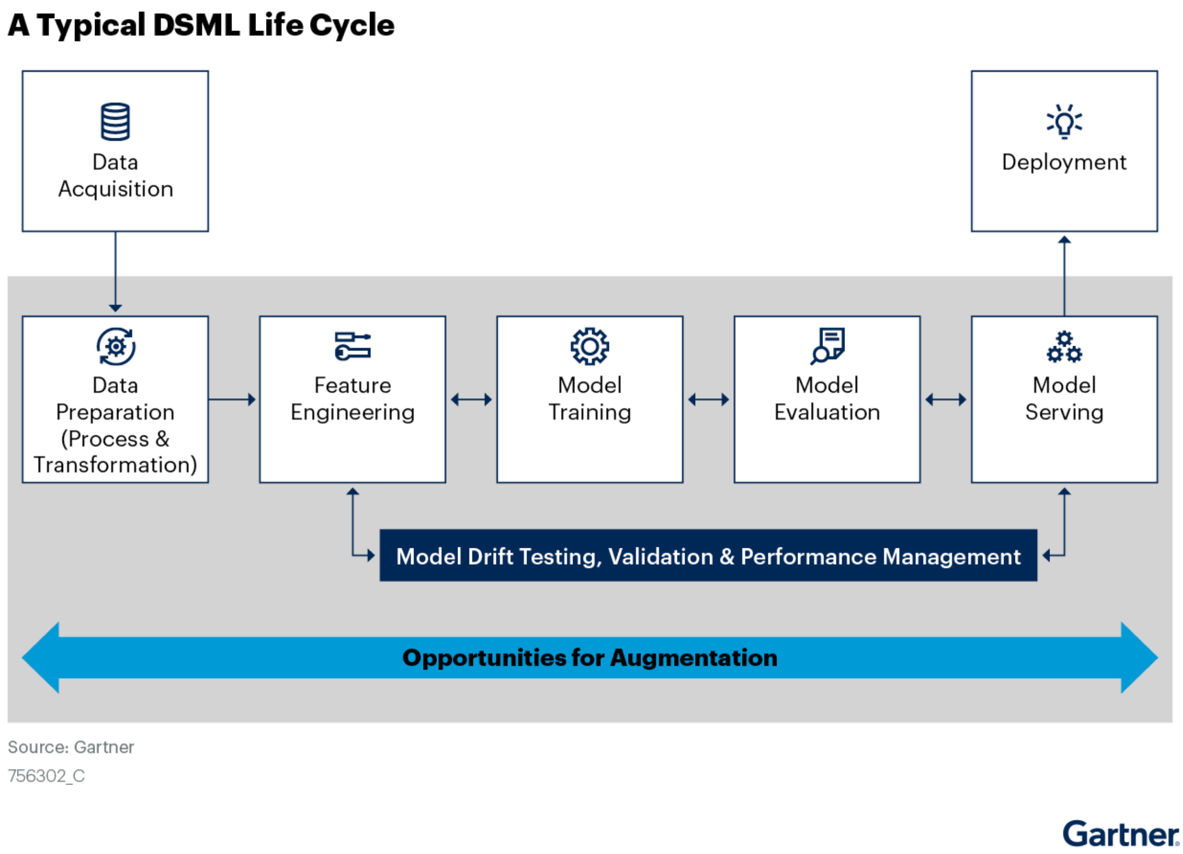
1. *Data Science and Machine Learning (DSML) becomes one of the core components of the data and analytics continuum. As organizations are looking to build their data science teams, they strive to bring in the right balance with a good mix of traditional data scientists and citizen data scientists. These are usually business domain experts who can understand and solve business problems more quickly, or engineers who can automate more quickly and not effectively have all the core data science skills.*
2. *Augmented DSML is primarily intended to break through the barriers of the complexity of data science platforms and offer limited support through extended capabilities, such as automation of particular tasks, and assist in the operationalization and management of DSML deployments.*
3. *Although there is an aspirational element to democratize everything, augmented DSML can only be used for a particular part of data science problems. Today, most automated capabilities are primarily designed to solve the most standard, repetitive tasks and solve common use cases.*
4. *Augmented DSML is now an integral part of almost every DSML vendor and solution, as they continue to add and expand such capabilities to DSML platforms. At the least, they can serve as a foundation to build prototypes to accelerate model creation and development. There is also an increasing trend of Augmented DSML being included in ABI platforms.*
5. *Augmented DSML must be viewed as a complementary component of broader DSML solution deployment. It is impractical to automate processes involving advanced capabilities and create the highest quality models. There is a good reason to call them "augmented" (i.e., enable, assist and support in multiple areas of the data science initiatives to accelerate and not replace data scientists' knowledge and expertise.*
6. *Augmented DSML is never intended to replace human talent or automate the entire DSML life cycle management. It simply enables organizations to DSML accessibility, use them to accelerate and scale DSML to meet customer demands.*

More details are covered in the section "Understanding the role of Augmented DSML" and beyond.

Overview

A typical DSML project life cycle includes several steps, such as data ingestion, data cleansing, feature selection or feature engineering, model selection, parameter validation, and optimization and model validation. The following is the sample illustration of those steps (see Figure 1).

Figure 1: A typical DSML Life Cycle



As we review each step, most of these processes are manual, time-consuming and repetitive. However, each of those steps provides unique opportunities for augmentation, and the level of augmentation can vary at each step based on the level of complexity involved in the DSML process. The goal is to best leverage augmented DSML rather than automate everything to save time, cost and overall performance.

Augmented DSML aims to improve the construction of ML applications by reducing the burden on humans and the need for expert knowledge. As a result, many organizations attempt to replace DSML expertise with augmented DSML functionality.

This research reviews how to best leverage augmented DSML into your initiatives and answer the following questions:

- **What are some of the key opportunities and benefits of using augmented DSML?**
  - *Refer to the section in the document on "Understanding the Role of Augmented DSML," and the detailed graphic on "Role of Augmented DSML."*

- **How to integrate augmented capabilities into your DSML process and initiatives?**
  - *Refer to the section on "Understanding How to Apply Augmented DSML in Each of These Stages."*

- **How to complement augmented DSML into your data science projects?**
  - *Refer to the detailed section "Complementing Augmented DSML With Your Data Science Initiatives"*

- **What are some of the applied use cases and case studies?**
  - Refer to the section "Complementing Augmented DSML With Your Data Science Initiatives" in this document where multiple use cases with examples were discussed.

- **How is augmented DSML offered, delivered and serviced by different vendors?**
  - Refer to the section "Categorizing DSML Vendors Based on Augmented DSML Functionality," where we categorized five major areas.

- **How can different personas leverage and benefit from augmented DSML capabilities?**
  - *Refer to the section "Benefits of Augmented DSML Capabilities to Leverage by Different Personas" for more details.*

- **What are some of the limitations, performance and architecture implications with augmented DSML?**
  - *Refer to the sections "General Limitations," "Performance Implications" and "Architecture Implications," where we highlighted some of the details.*

- **What are some of the strengths and weaknesses of augmented DSML?**
  - Refer to the sections “Strengths,” “Weaknesses” and “Guidance” for detailed insights.

Need for Augmented DSML

DSML-based solutions had demonstrated success at improving efficiencies related to organization, decision making and process. Still, they hadn’t demonstrated much success at improving the efficiency of ML itself without significant expertise — until the emergence of Augmented DSML. The process of building, deploying and managing DSML workloads has crippled many project initiatives, and executives and business leaders are demanding greater automation and operational efficiencies from DSML through augmentation.

Many organizations continue ranking the shortage of staff skills as one of the barriers to ML adoption. Executives and business users are eager to explore what the augmented DSML can offer to democratize ML for nontechnical business users and offset the skills shortage. Many technology vendors supporting augmented DSML functionality market that their offerings can allow everyone to build trusted models — including domain experts who are not data scientists.

Augmented DSML provides a unique opportunity for organizations to drive productivity and deliver competitive advantage with accelerated model building, training and deployment.

The organization is now embracing automation through augmentation for transformation in ML workflows as a new way to meet the growing customer demands. New capabilities and diversity on the augmented DSML tools allow more users to work and find solutions to the DSML problems, beyond traditional data scientists.

Depending on the organization’s maturity, augmented DSML can be used for selective and narrow use cases delivering specific, measurable business value and managing complete end-to-end management of such ML workflows. However, domain knowledge and business integration expertise cannot be replaced by Augmented DSML.

Understanding the Role of Augmented DSML

As we try to understand the role of the augmented DSML, it is important to note that augmented DSML aims to automate DSML initiatives — including their ML pipelines and processes.

Most of the DSML initiatives where the augmented DSML process is followed will fall into either an intermediate or generalized category. The intermediate category aims to automate ML pipelines fully but requires human intervention, while the generalized category represents fully automated ML.

The intermediate category can offload overhead from DSML experts. Still, it cannot fully eliminate experts' intervention — especially when dealing with ML technique selection and parameter configuration. By contrast, generalized category refers to fully automating ML without DSML expertise or involvement. Gartner recognizes generalization as a transformational technology and a form of artificial general intelligence (AGI), which is at least eight to ten years away from mainstream adoption.

While augmented DSML intends to automate the entire end-to-end process of applying ML to real-world problems, there is a lot of ambiguity around how best to define the end-to-end process. It can differ from one DSML initiative to the next, depending on the business process and the extent to which domain understanding and application integration are needed.

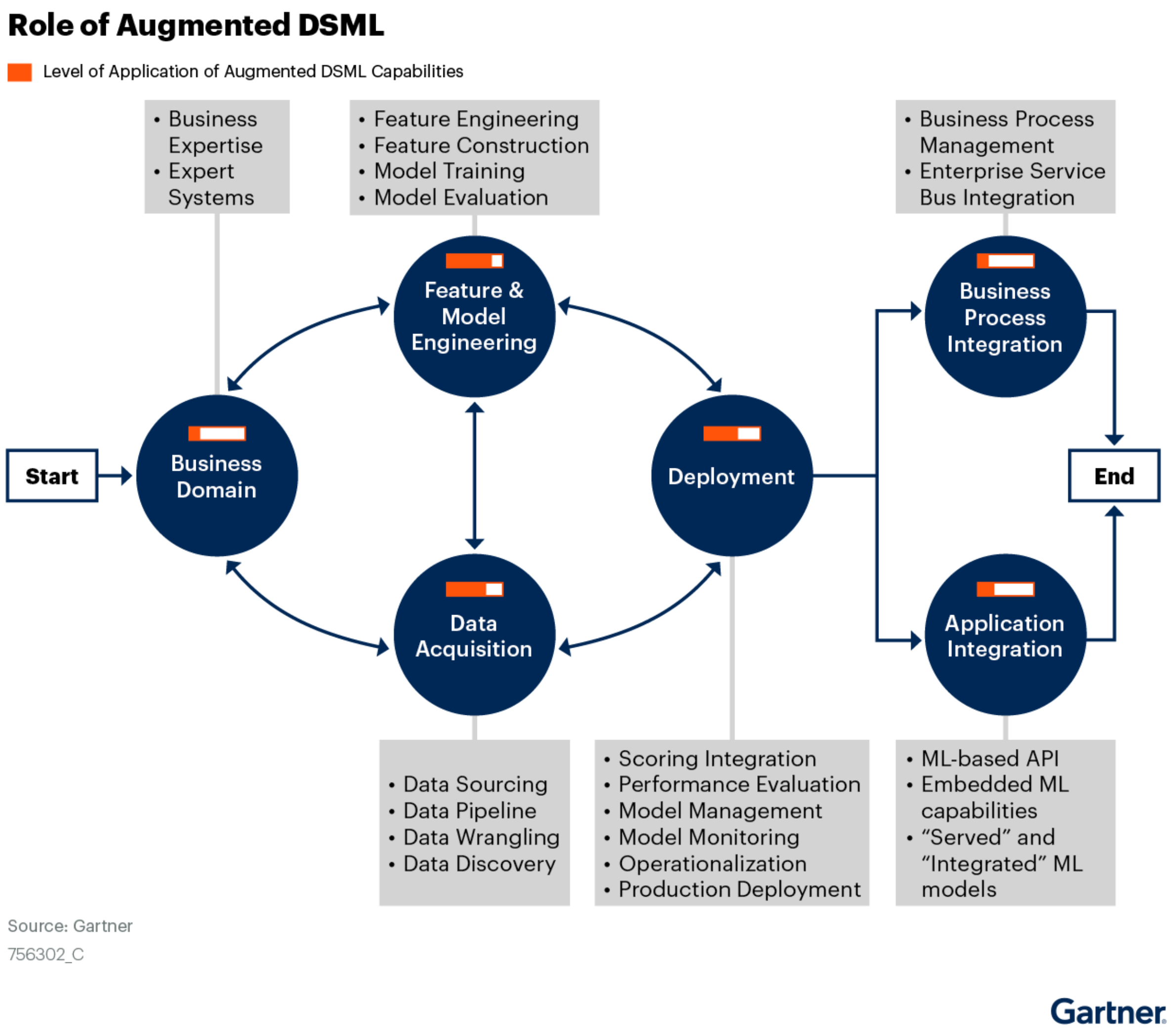
The development methodology used plays a critical role in determining the impact and success of your ML initiatives. The following are some common development methodologies used in DSML initiatives:

- **Cross-Industry Standard Process for Data Mining (CRISP-DM),** which was traditionally used to support data mining projects through stages, has extended to support broader data science projects.
- **Sample, Explore, Modify, Model, Assess (SEMMA)** is often used for quick prototyping in DSML initiatives.
- **Knowledge Discovery in Databases (KDD)** is a broader methodology that focuses on using data-mining techniques to support knowledge discovery. Like CRISP-DM, it has also been extended to support DSML initiatives. KDD often includes portions of CRISP-DM and SEMMA.
- **Team Data Science Process (TDSP)** focuses more on team collaboration and agile development in data science initiatives.

Any of these methodologies can leverage the augmented DSML functionality as part of their process. We, however, will focus specifically on the TDSP life cycle developed by Microsoft in this research note because of the stronger emphasis on business domain understanding, and the business process management or application integration.

Figure 2 below summarizes the stages typically involved in DSML initiatives and assesses the application of augmented DSML capabilities at each stage, based on the TDSP life cycle.

Figure 2: Role of Augmented DSML



The stages within specific DSML initiatives include:

- **Business domain:** An understanding of the business domain on how an area of the organization creates, delivers and captures value in economic, social, cultural or other contexts.

- **Data acquisition:** A data strategy for delivering clean, high-quality data and understanding how the data relates to the model objectives. This stage typically involves the use of data management principles to support model objectives. For more information, refer to how to Create a Data Strategy to Ensure Success in Machine Learning Initiatives.

- **Feature and model engineering:** The process of building DSML workloads to support the creation of ML models. For more information, refer to A Guidance Framework for Operationalizing Machine Learning.

- **Deployment:** The deployment process involves selecting the right technology, implementing a strategy to operationalize DSML artifacts into diverse environments and performing ongoing maintenance and management of production models. For more information, refer to Implementing an Enterprise Open-Source Machine Learning Stack.

- **Business process integration:** Many DSML output artifacts blend directly into business processes that, for example, integrate through an enterprise service bus (ESB).

- **Application integration:** Many DSML output artifacts deploy directly into software applications. For more information, refer to Integrating Machine Learning Into Your Application Architecture.

Understanding How to Apply Augmented DSML in Each of These Stages

As noted, augmented DSML cannot automate an end-to-end DSML life cycle that includes business domain understanding and business process or application integration. Some areas benefit readily from the application of augmented DSML while other areas — ones that require business domain expertise — lag behind.

Business Domain

Augmented DSML cannot automate the ability to understand a business domain because it is entirely dependent upon input data that is highly heuristic (intuitive judgment) and involves self-awareness. There are some areas where Augmented DSML complements heuristic learning, but this progress is insignificant to date.

The process of capturing, developing and managing business plans across different organizations within the business to support the application of ML is a significant component of any DSML initiative.

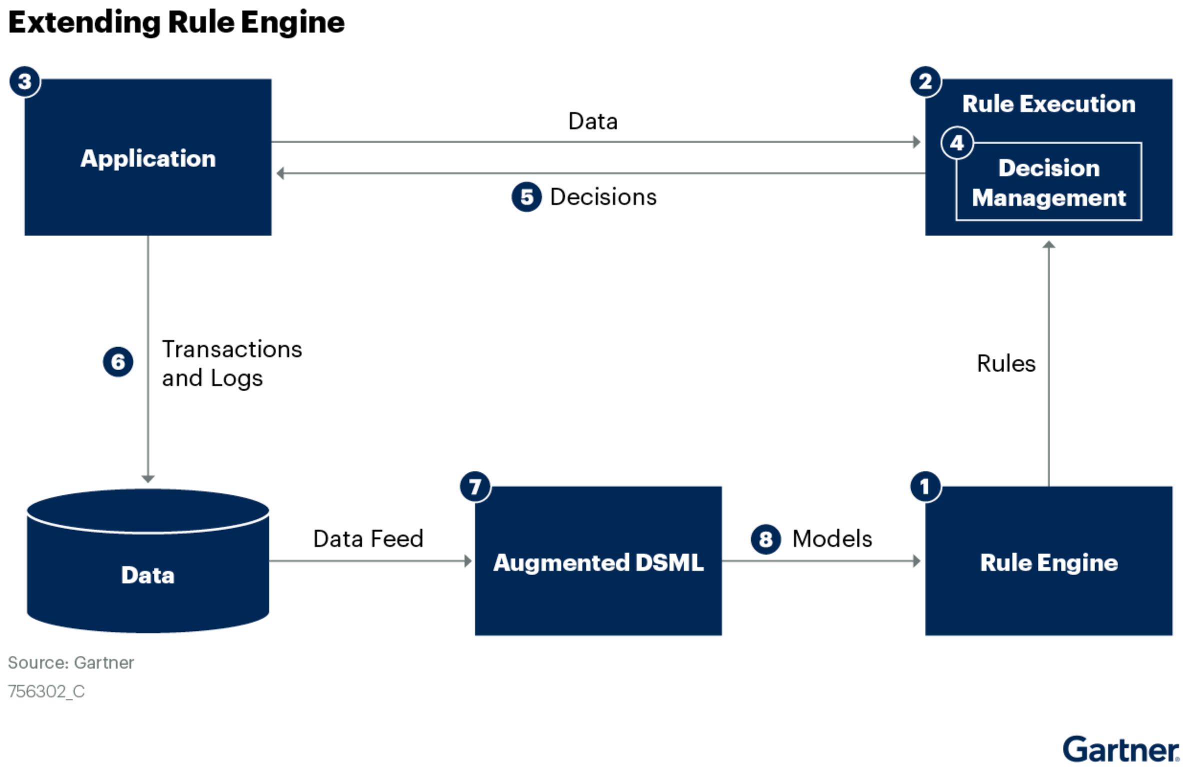
According to the TDSP life cycle, this process is key to understanding relevant variables and data sources that the business has access to or needs to obtain. Thus, Gartner recommends that all DSML initiatives start with the proper business domain understanding.

Business domain understanding is a highly heuristic process, where business matter experts obtain knowledge over time through experience and intuition and, in many cases, explicitly record that knowledge in a knowledge base or rule-based engine. For example, pilots often revert to a “rule of thumb” or a “grain of salt” rule when evaluating the performance data in an aircraft manual. The aircraft manufacturer may not make any allowances for varying degrees of pilot proficiency or the aircraft’s mechanical deterioration. Therefore, human judgment and intuition are required. It is vital to note that the skills they bring into the table are so unique, the tools won’t be able to close that gap. The domain expertise that they possess is often far superior even beyond the data scientists. Thus, it is the combination of the domain expertise and the platform that can make the DSML superior.

Heuristic methods, such as human expertise, experience, judgment and intuition are far more sophisticated than current ML capabilities. As a result, augmented DSML does not play a big role in business domain understanding using heuristic methods. However, it can support the extension of knowledge base or knowledge graph use cases. For more information on this topic, please read Graph Technology Applications and Use Cases.

One of the techniques commonly used to support business domain understanding is a knowledge graph or rule-based system. These systems extend the use of augmented DSML and the order in which it interacts with the rule engine, as illustrated in Figure 3.

Figure 3: Extending Rule Engine



Although augmented DSML can support the extension of the business domain knowledge, it is not yet ready to substitute human judgment in developing business domain understanding. Vendors like IBM and InRule Technology focus on how to best leverage augmented DSML to extend rule-based engines.

Data Acquisition

Augmented DSML scores very well in augmenting data acquisition and understanding. Numerous technology vendors are emerging in augmented data management, which improves the ability to automate the data management portions of the DSML pipeline.

Typical data acquisition processes include ingestion and acquisition of data, exploring them to determine data quality and fit for modeling, and establishing a pipeline to feed DSML workloads continuously. Augmented DSML has performed exceptionally well at those tasks. Much of the success in data acquisition and understanding is partly due to the emergence and accomplishments of variations of augmented analytics. In many cases, augmented analytics leverages augmented DSML to enhance and accelerate data management — including the acquisition of data, the profiling or exploration of data, and the operationalization of data. Some of the popular tools include Altair, Alteryx, Paxata, Trifecta, Unify and others.

The range of capabilities of these tools extends from self-service data preparation, data integration and data management, data wrangling, enterprise data catalog to augmented analytics. These tools also offer complete automated capabilities on several ranges, such as normalizing datasets as part of data management, profile datasets, interpret data across multiple sources identifying relationships and score relevancy. However, the emergent capability driving much of the progression in data acquisition and understanding is the broader focus on augmented analytics.

Augmented analytics uses ML- and AI-based techniques to automate data preparation, insight delivery and sharing. It also includes augmented DSML to automate development, management and deployment. Gartner views augmented analytics as to the next wave of disruption in the data and analytics market. To learn more about augmented analytics, see Leverage Augmented Analytics to Drive Digital Business Model Innovation and Market Guide for Augmented Analytics Tools.

However, augmented analytics' contribution to DSML initiatives is its ability to automate data management refer to Feature Stores for Machine Learning (Part 1): The Promise of Feature Stores, Feature Stores for Machine Learning (Part 2): Current State and Future Directions and analytics (see Maximize the Benefits of Augmented Analytics With a Strategic Action Plan) to support and complement augmented DSML functionality. While some of the processes above require greater business or subject matter expertise (e.g., analyzing data), augmented analytics aims to leverage ML- and AI-based techniques to reduce the dependencies of human experts.

Feature and Model Engineering

Most of what you hear about in the augmented DSML world relates to automating the model engineering process. Model engineering is the most mature automated functionality of ML today, with the majority of augmented DSML offerings supporting some form of feature engineering and model engineering.

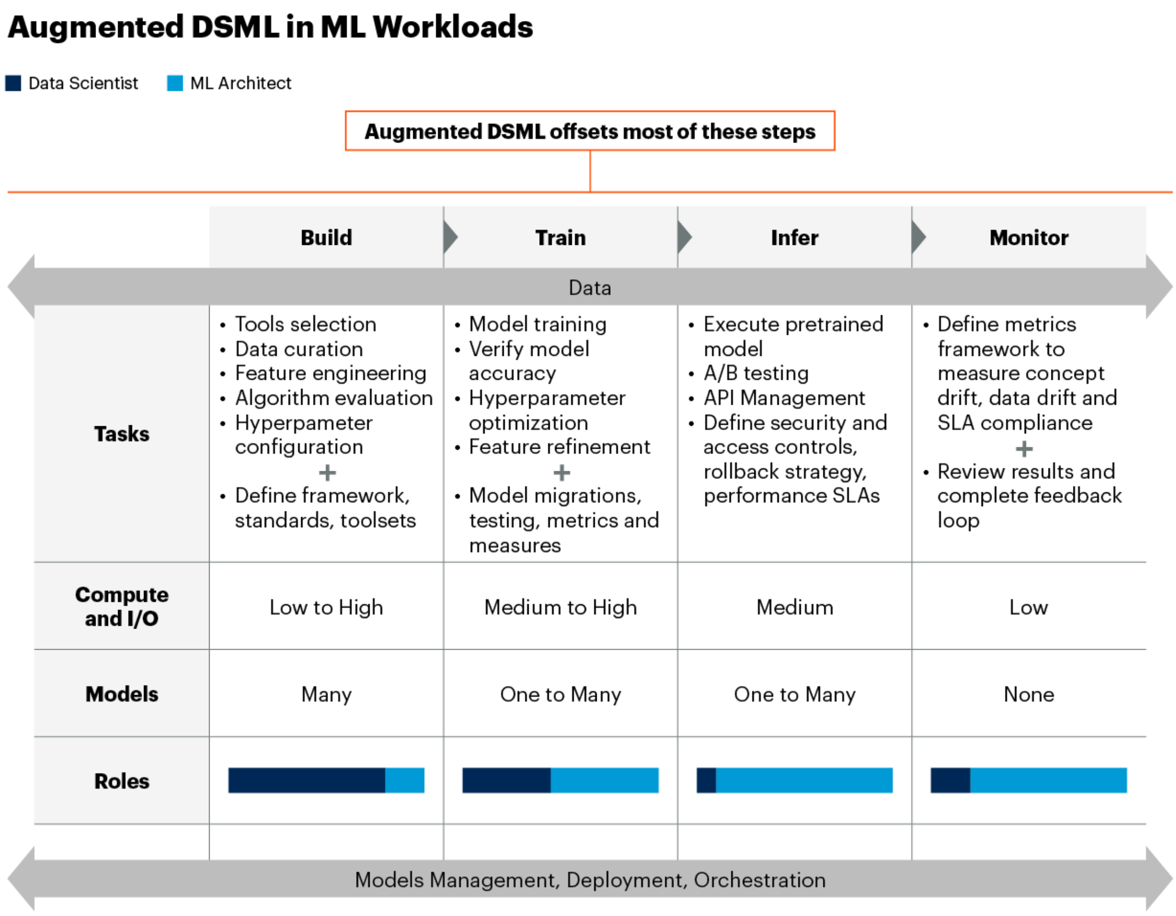
The model engineering process gains the most benefit from augmented DSML. This stage contains the processes associated with building and managing ML workloads. Many vendors that associate themselves with augmented DSML functionality support this stage of DSML initiatives. Some of the common tasks include:

- Feature engineering, which is the process of using domain knowledge to develop features for many ML algorithms. Feature engineering is also considered a form of preprocessing and, as a result, can be used as a data acquisition method.
- Model selection, which is the process of selecting the appropriate model to support the algorithm.
- Feature selection, which helps determine the features and variables for input in the model creation.
- Model tuning, which is the process of optimizing the model.
- Model training, which is the process of training data to support the model.

DSML experts primarily train and tune algorithms to support ML model engineering. The training and tuning process includes finding the right set of parameters, methods and functions to make predictions on new data. By iteratively examining functions and methods to automate model engineering, augmented DSML offloads much of the training and tuning effort from experts.

However, automating the model engineering process may also involve automating the ML workload process. Figure 4 illustrates the use of augmented DSML in DSML workloads).

Figure 4: Augmented DSML in ML Workloads



Source: Gartner
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Gartner

Model engineering primarily focuses on the "build" and "train" phases of an ML workload process, as shown. However, the entire ML workload process is mostly offset by augmented DSML. For example, DataRobot automatically builds, trains and infers based on uploaded data provided by the user. The augmented DSML functionality abstracts the model engineering processes away, allowing users to focus more on the data analysis.

There are numerous methods, libraries, toolkits and systems supporting feature creation, algorithm selection and hyperparameter configuration for the build tasks. For example, NAS is a technique often deployed for building artificial neural networks.

Model training automation, optimization and refinement are some of the common functionality offered by augmented DSML in managing DSML pipelines. For example, H2O.ai provides an interface that automates training and tuning a selection of candidate models.

Model Inference is the prediction or output from a trained model. It includes evaluating quality (accuracy of the prediction) and latency (how fast the predictions are provided). An example of automating the inference phase is Google's AutoML functionality, which transfers learning from existing augmented DSML architectures.

Monitoring is still fairly immature in augmented DSML. There are efforts to monitor ML models for drift and other conditions. For example, Dataiku's ML platform supports automated model monitoring, which enables automated discovery of low-fidelity ML models and accelerates model life cycle management.

Deployment

Augmented DSML is rapidly emerging in the deployment phase through libraries, toolkits, and, more recently, system/platform-level providers like DataRobot, demonstrating extended interest in integrating augmented DSML platforms with the ML operations (MLOps) community. However, in terms of diverse deployment options — such as loading models directly into applications — augmented DSML suffers in the absence of MLOps platforms.

Augmented DSML in deployment involves leveraging ML and automated processes to monitor models and pipelines and deploy them into production, i.e., to "operationalize ML models or services." Deployment is typically the bottleneck between data scientists and the IT engineers responsible for putting ML models into production. However, Augmented DSML is emerging as a key capability for helping organizations deploy ML models into production.

To assess the impact of augmented DSML on the deployment stage of ML initiatives, Gartner examined three areas:

- **ML model deployment:** Deploying ML models via augmented DSML functionality is possible and is growing in popularity. The more popular approach leverages model-hosting services through API/HTTPS endpoints and is common in platform services, such as Amazon SageMaker and Azure Machine Learning.

- **Deployment details and performance statistics:** Augmented DSML can be used for collecting deployment details and performance statistics by leveraging ML algorithms that monitor other ML algorithms. For example, many Gartner clients use anomaly detection algorithms to monitor other ML algorithms. This scenario of "ML on ML" can be automated to support the deployment of ML-based applications in real-world environments.

- **Automated model performance management:** Some Augmented DSML features leverage ML to self-govern and manage model performance, and is another example of ML being executed on ML to aid in deploying ML-based applications.

Business Process Integration

Use of augmented DSML in business process integration is gaining momentum, thanks to the emergence of custom-made and commercial off-the-shelf software that specialize in specific business functions. This new offering aims to improve business processes by providing customized solutions in support of a business function.

Leveraging augmented DSML in business process integration is a cumulative effort. It involves interacting with human experts since a business process may require a series of steps and human intervention to achieve an outcome. The augmented DSML functionality blends into business process workflows, augmenting much of the ML overhead where the result can be an improved business process that is faster and more transparent. For example, some banking and finance organizations reinvent the underwriting process with automated risk management that specifically targets mortgage lending.

Application Integration

Augmented DSML in application integration and software engineering processes still has a steep hill to climb since it will depend on various factors that are specific to the use case and type of ML workload. In addition, certain aspects of DSML initiatives are fundamentally different from prior software application domains, making it difficult to leverage augmented DSML for those engineering challenges. However, using augmented DSML to load models directly into an application is gaining some traction — especially from some of the mega cloud vendors that offer augmented DSML services as part of their core offerings.

Integrating augmented capabilities in software engineering services and application integration is a new area that is gaining relatively lower adoption. As we reviewed previously, there are plenty of opportunities for augmented DSML for building and managing DSML workloads — but few options exist in application software citizen development and engineering processes. However, there are plenty of methods for using broader ML functionality to support application development and application integration. APIs, open-source frameworks and cloud services continue democratizing ML technologies to the application developer.

Categorizing DSML Vendors Based on Augmented DSML Functionality

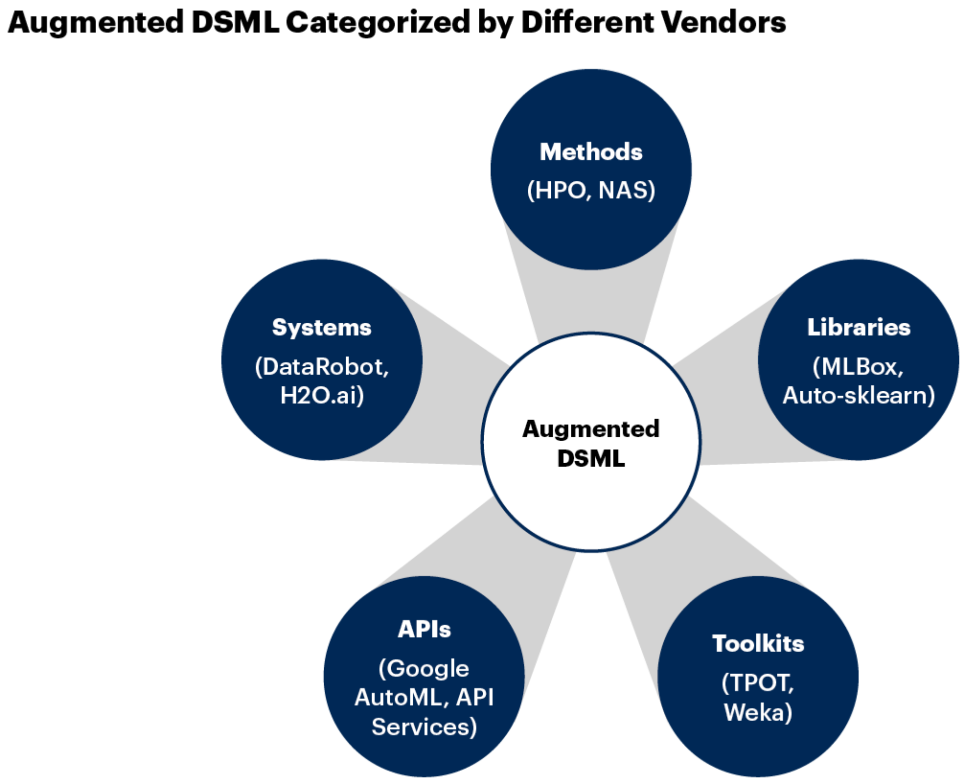
Augmented DSML is rapidly emerging as a critical component to augmenting analytics and intelligent automation. However, many technology vendors often provide ambiguous descriptions of their augmented functionality and capability, making it difficult to assess the impact of their productivity.

To further understand the augmented DSML, the core functionality can be broken down into five categories as presented by vendors, solution providers and use cases.

Categorizing them based on the functionality also provides an approach to using augmented capabilities for solving specific business challenges for your implementation.

The following figure provides an overview of the vendors, solution providers and use cases determined by the augmented DSML functionality (see Figure 5).

Figure 5: Augmented DSML Categorized by Different Vendors



Source: Gartner
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- **Methods:** Methods are procedures associated with a task within the ML pipeline. For example, hyperparameter optimization (HPO) is an augmented DSML method commonly used for tuning models. Additionally, neural architecture search (NAS), like HPO, is a method for automating artificial neural networks (ANNs). Numerous methods are emerging to aid in the development of more sophisticated ML-like deep neural networks. One such method uses transferable augmented DSML to design deep neural networks for specific tasks and datasets.

- **Libraries:** Augmented DSML libraries are collections of methods (i.e., code) and open-source software packages that DSML experts can call to automate different tasks within an ML pipeline. Leveraging these libraries typically requires knowledge of general-purpose programming languages. For example, MLBox is an automated ML Python library that includes multiple features and HPO.

- **Toolkits:** Toolkits contain sets of libraries that help DSML experts create and deploy augmented functionality into specific runtime environments. They typically operate at a higher level of abstraction than libraries. Microsoft, for example, offers an open-source toolkit for neural architecture search and hyperparameter tuning.

- **APIs:** Augmented DSML has application programming interfaces (APIs) available for building, training and predicting DSML workloads. Technology vendors often advertise them as "no model code required APIs." These APIs are typically repurposed functions to support multiple tasks and, in many cases, they rely on different forms of knowledge acquisition and transfer learning. For example, Google's AutoML Vision API generates predictions on images, and relies primarily on transfer learning to leverage knowledge from previously trained models.

- **Platforms:** Augmented DSML systems are broader ML platforms (often proprietary) that focus primarily on fully automated functionality. Some examples include DataRobot, H2O Driverless AI, Dataiku and DSML platforms offered by Google, AWS, Microsoft, IBM, Oracle and others.

For more guidance on comparing augmented DSML functionality among key vendors, refer to Solution Criteria for Data Science and Machine Learning Platforms and vendor-specific scorecards with interactive side-by-side comparison using our cloud decisions tool to specifically review the augmented functionalities and capabilities offered by these platforms.

Complementing Augmented DSML With Your Data Science Initiatives

Augmented DSML aims to automate data preparation, modeling and tuning steps that make data science more accessible to business experts — thereby helping enrich the quality of many models, more than the technical skills of the data scientists. In standard data science initiatives, we see data scientists use 70% of their time in data and model preparation. Once built, only a fraction of their time is spent on testing and tuning. Testing and tuning model parameters have become commodities, and performance is driven by data selection and preparation — one of the areas that are best suited for augmented DSML.

By successfully incorporating DSML into the analytic process, organizations can drive the best and maximize the use of analytics. Augmented DSML is well-positioned for those who want to take advantage of its full spectrum of capabilities. Organizations can also use augmented capabilities to streamline common tasks with certain goals, metrics and outcomes — and leverage automated models. Engage expert data scientists to move beyond their traditional ambit to value-added activities, such as enhancing fairness and building trust in the outcomes of ML models.

Provisioning and complementing augmented DSML capabilities with ML initiatives can occur in several ways:

- As a Service
- As a stand-alone DSML platform
- As an extension to your existing DSML platform
- As a custom platform using open source technologies

The ultimate goal is to apply the augmented DSML solution that helps experts and non-technical business users improve on streamlining and automating certain processes, and develop more efficient and accurate models of DSML initiatives. To learn more, see Four Real-World Case Studies: Implement Augmented DSML to Enable Expert and Citizen Data Scientists.

The following are the examples of the use of Augmented DSML in predictive, machine learning and artificial intelligence use cases.

- Predictive examples include estimating the cost of the life insurance, forecasting the efficiencies of the supply chain and improving the marketing outreach to reduce the customer churn. They also create opportunities for the propensity to buy more products, predict wait times for customer service, food delivery based on the patterns of past usage, etc.

- Machine learning examples include the use of fraud detection based on spending patterns, collecting data through search engines and tagging to increase brand awareness, use of voice assistants and dynamic pricing for delivering personalized services, etc.

- Artificial Intelligence examples include the use of supervised, unsupervised and reinforcement learning on self-driving automobiles, facing recognitions and patterns, use of natural language processing and conversational platforms in sales, supply chain management and other customer-facing services.

Organizations need to review and test multiple vendors' solutions to determine the best fit for your results and, at times, it can vary by use case. Each solution will require a different set of processes and the choice of algorithm to follow based on the user interface, maturity of the platform and the extended capabilities that are offered through other services. Some vendors only offer default capabilities, whereas others allow customization to best suit your project-specific needs. There are also vendors that offer such services for specific industries and use-cases. It is also important to consider other factors like costs, the accuracy of results, calculation times, ease of use, and handling to complement the augmented DSML solution.

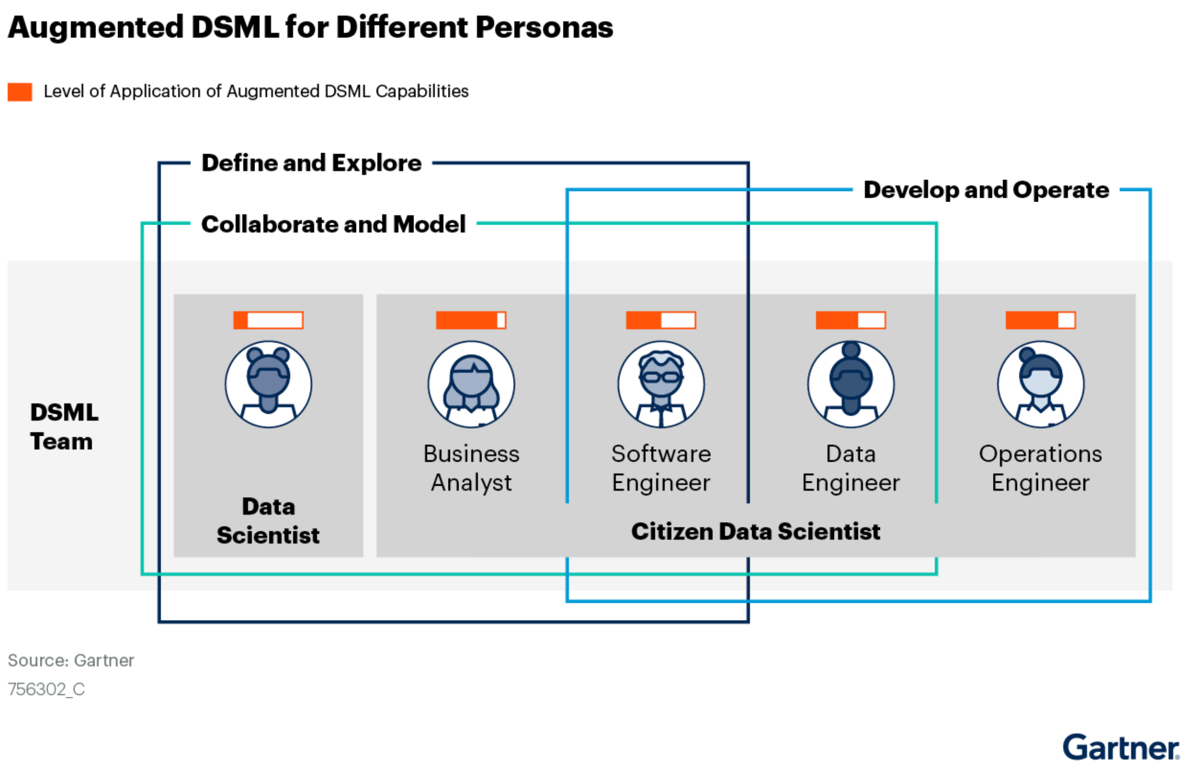
Benefits of Augmented DSML Capabilities to Leverage by Different Personas

Establishing and maintaining communication with collaboration remains a critical aspect for DSML teams. It is important to create a clear narrative to guide decisions and develop your team to contribute and scale on demands incrementally.

DSML has transformed into a multidisciplinary field to explore data, extract insights and create powerful products. As more and more citizen data scientists are getting involved in these DSML teams, it creates greater opportunities to leverage augmented DSML capabilities.

Figure 6 provides the different personas that are involved in a typical DSML team and the level of augmented DSML capabilities that they can leverage at each stage of the DSML life cycle.

Figure 6: Augmented DSML for Different Personas



It is vital to building the DSML capabilities of your organization through a data science community of practice. Communities of practice are stable, informal and voluntary structures organized around the knowledge of diverse user communities — including business analysts, data scientists and AI engineers.

To learn more about the types of skills required for deploying ML-based projects, please see Essential Skills for AI Engineers, Essential Skills for Machine Learning Architects and Essential Skills for Citizen Data Scientists.

Limitations, Performance and Architecture Implications With Augmented DSML

Augmented DSML is gaining success in some applications, like many supervised learning requirements. However, there is still much work to be done in other, more complex requirements that need to solve different problems. The following are some of the areas where augmented DSML have demonstrated challenges among Gartner clients:

General Limitations

- Augmented DSML can be great for prediction, but it cannot preprocess consistently to outperform human data scientists, as humans are natural learners who can adapt quickly to new or changing tasks periodically. Data Scientists will continue to add value by providing well-featured engineered datasets to augmented DSML platforms.

- Augmented DSML is good at building models. However, it cannot be operated as a stand-alone and must always be combined with data scientists to define requirements and business problems, as well as define and generate features for strong, predictive outcomes and valuable insights.

- Augmented DSML is limited in its capability in areas where the feature engineering and the corresponding ML process rely on incorporating domain knowledge, imagination, creativity and expertise that only human experts can offer. Even within that, the performance and outcomes of these DSML processes can vary based on the skill set and domain expertise of the data scientists.

- Augmented DSML may not work on models that involve unsupervised learning and reinforcement learning processes. These approaches do not rely on labeled datasets or conduct step forward functions from their actions. It can also deal with a limited set of problems, such as classification and regression, but currently cannot accurately build recommendations and ranking of models or draw actionable insights.

- Although augmented DSML has extended its ability to handle various data types such as relational, structured, text, images, time series, etc., it still has limitations when dealing with custom or complex data type format.

Performance Implications

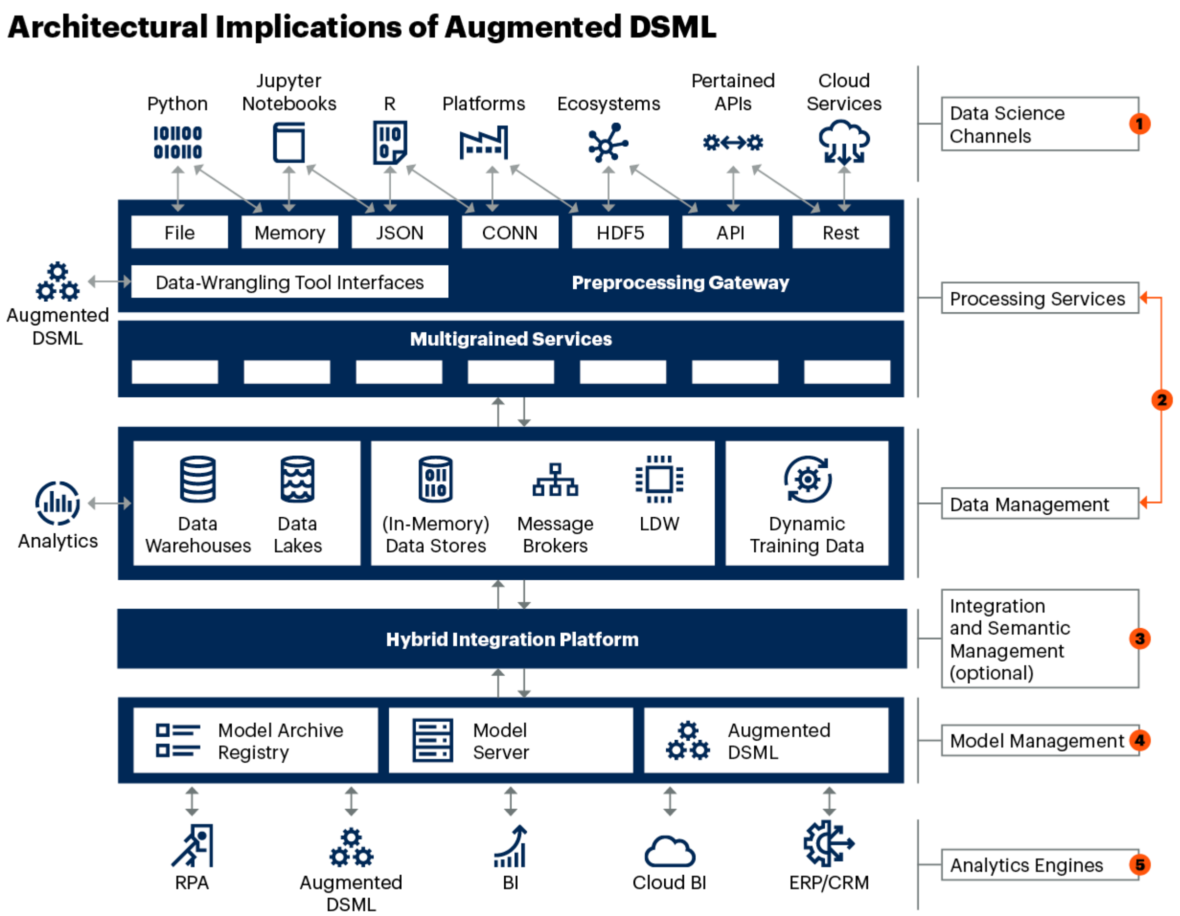
Augmented DSML architecture represents the foundations, components and configurations upon which users conceive an ML capability. Depending on the level of sophistication, the architecture can have a major impact on ML applications' sustainability and ongoing maintenance. The widespread application of more sophisticated augmented DSML, such as NAS for building ANNs, will most likely change the landscape of computation much more than traditional model development. As a result, there is a trade-off between the compute needed to support augmented DSML functionality and the labor of a data scientist. Regardless, any level of using augmented DSML functionality is worth the investment. Some technology vendors additionally support the ability to perform low-level capacity planning, which helps determine the performance suitability of certain functionality to avoid excessive expenses for the compute used to execute augmented DSML functions.

Architecture Implications

Augmented DSML is rapidly evolving and has enormous potential to expand as compared to classical DSML. Technology vendors are motivated to explore augmented functionality to democratize DSML activities. Much of the effort thus far has focused on selecting algorithms on the top end, and optimizing and tuning output at the bottom. ML architects play in bridging this gap (i.e., designing architectures that support scalable deployment options is only beginning to be explored).

The architecture of Augmented DSML systems cannot be an afterthought, and it may vary from classical DSML architecture depending on the organizational structure and use case. A well-designed system will support more DSML channels (connected to a common data preprocessing gateway) and model engineering capabilities than classical ML architectures. As a result, a larger number and variety of users may execute this capability.

Figure 7: Architectural Implications of Augmented DSML



Source: Gartner
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Augmented DSML affects five layers in the ML architecture, as shown in Figure 7.

1. DSML channels to integrate augmented DSML bots through multi-grained services. For example, the architecture may integrate augmented DSML bots with customized Python code to generate ensemble models.

2. Preprocessing services and a data pipeline management system. For example, the architecture may enable augmented DSML bots to leverage the same preprocessing techniques as other DSML channels to support dynamic training data.

3. An integration platform to manage custom ML models from public APIs trained on internal data. For example, the architecture may leverage augmented DSML APIs to add new data to a project’s dataset dynamically.

4. An enhanced model management system that supports various model-serving (i.e., prediction) techniques and manages catalog augmented DSML APIs to support various business objectives. For example, the system may maintain a host of augmented DSML vision APIs to support various recognition applications. By managing augmented DSML APIs, the system supports transfer learning, which enables organizations to repurpose existing augmented DSML APIs for different tasks.

5. An integration platform to support multiple analytics engines. For example, the architecture may access augmented DSML functionality from various legacy analytics engines.

Compared with traditional ML architectures, augmented DSML poses unique challenges to efficient execution. Augmented DSML requires a much larger storage capacity, produces irregular memory accesses and consists of a diverse set of performance bottlenecks. Many of the requirements depend on the ML platform or technology used. For example, many services allow for local CPU processing, while others require a cloud platform with computational fees. Therefore, strategic capacity planning must address CPU/GPU usage, execution time, memory and storage limitations.

Gartner clients utilizing augmented DSML functionality can deploy their models quicker into production. However, the optimal platform and runtime configuration varies based on the performance target and the ML model executed.

Strengths

- **Creates an accessible and collaborative environment for everyone:** Data science and ML development have become more accessible and collaborative to citizen data science roles, such as business analysts, developers and others with augmented DSML. This occurs while empowering data science experts to be more productive and focus on creative, high-value tasks and advanced functionalities in their model deployments.

- **Faster time to delivery with improved accuracy and efficiency:** Gartner clients have found success in deploying augmented DSML functionality to reduce development life cycles, improve accuracy, accelerate the delivery of their ML-based systems and enhance process automation. We also have evidence of expert data scientists using these tools for faster time to insight and to test/eliminate bias.

- **Augment DSML is now an integral part of almost every DSML vendor solution:** As vendors continue adding and expanding such capabilities to DSML platforms, organizations see greater adoption of augmented DSML to build prototypes to accelerate model creation, development and deployment.

- **Greatly complements the broader DSML solution deployment**: There is a good reason to call them “augmented” i.e., enable, assist and support in multiple areas of the DSML initiatives to accelerate and not replace data scientists’ knowledge and expertise.

Weaknesses

- **More work needed for mainstream deployment and complete autonomy:** In spite of augment DSML providing game-changing opportunities, impacting analytics and automation in terms of new business opportunities and IT productivity, more work is needed to match the pace of the evolving data science domain before it can become mainstream, and for the complete autonomy of human experts. Some augmented DSML solutions are considered ‘black-box’ and don’t allow insight into the back-end algorithms, which may pose an issue for organizations that need to deliver details on outcomes.

- **Restrictive to standard, repetitive and common use cases:** Although there is an aspirational element to democratize everything, augmented DSML can only be used for a particular part of the data science problems. Most automated capabilities are primarily designed to solve the most standard, repetitive tasks and solve common use cases.

- **Limited scope and performance:** Augmented DSML is limited in its capability in areas where the feature engineering and the corresponding ML process rely on incorporating domain knowledge, imagination, creativity and expertise that only human experts can offer. Even within that, the performance and outcomes of these DSML processes can vary based on the computational needs, skill set and domain expertise of the data scientists.

- **Not suitable for certain model development processes:** Augmented DSML may not work on models that involve unsupervised learning and reinforcement learning processes. These approaches do not rely on labeled datasets or conduct step forward functions from their actions. Also, it can deal with a limited set of problems, such as classification and regression, but currently cannot accurately build recommendations and ranking of models or draw actionable insights.

Guidance

Organizations investing in augmented DSML platforms serve a clear benefit and advantages for businesses, enabling them to be more customer-centric, innovative, collaborative and empower everyone to reap the benefits from it. Augmented DSML is changing the face of ML-based solutions by enabling a more diverse group of users to address business and operational challenges, and to improve the efficacy of existing ML-based systems.

Gartner clients have found success in deploying augmented DSML functionality to reduce development life cycles, improve accuracy, accelerate the delivery of their ML-based systems and enhance process automation. However, there is still much work needed in business domain understanding, collaboration with existing DSML experts, the performance of some model workflows and deployment into business processes.

The following are some of the guidance on augmented DSML that can help plan and manage your DSML initiatives:

- Avoid attempting to replace DSML experts with augmented DSML. Rather, position augmented DSML as a complementary functionality to reduce the overhead associated with development life cycles and validate existing modeled solutions' precision and accuracy.

- Leverage augmented DSML in custom-made software where it meets your less-sophisticated business objectives. Custom-made software offerings — such as ZestFinance used in financial underwriting — augment much of the business domain understanding, allowing users to focus more on the results and complex decision making. However, these are often proprietary, paid black-box services that may be difficult to rationalize. Therefore, Gartner recommends leveraging augmented DSML in custom-made software when the business objectives are well-defined and unambiguous.

- Integrate augmented DSML functionality through DSML channels that connect to the same preprocessing gateway. This enables users to validate the results of augmented DSML against custom-built solutions that use the same framework. Otherwise, it may become too difficult to compare results because of the contrast in the underlying data fabric.

- Perform capacity planning for larger, more sophisticated augmented DSML methods like NAS. Recent advances in more sophisticated augmented DSML methods demand tremendous computational resources and expense, which pose a barrier to entry for many organizations without access to large-scale computation. Thus, before embarking on sophisticated augmented DSML search methods, organizations should develop a strategic plan that addresses the search space needed. The capacity plan should evaluate training considerations against compute time. While there have been many methods to improve the performance of more sophisticated augmented DSML methods, capacity planning is still required to ensure an acceptable performance threshold for your environment.

- Outsource augmented DSML to interoperable platforms when you have already made investments in ML platforms. There are many ways to add augmented DSML functionality to existing environments. For example, AI and analytics platforms like C3 AI and Cloudera-Hortonworks fully integrate (and often collaborate) with DataRobot to provide AutoML functionality to their existing ecosystem.

Document Revision History

Augment Data Science Initiatives With AutoML - 30 August 2019

Recommended by the Author

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

How Augmented DSML Makes Data Science Projects More Efficient

A Guidance Framework for Operationalizing Machine Learning

Comparing AI-/ML-Based Systems That Minimize Data Science Requirements

Machine Learning Training Essentials and Best Practices

Navigating Differentiated Features in Data Science and Machine Learning Platforms

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