



Omdia Decision Matrix: Selecting an Enterprise ML Development Platform, 2020–21

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Summary

Catalyst

The digital transformation sweeping through most businesses includes the latest breakthroughs in machine learning (ML), a branch of artificial intelligence (AI). ML and, in particular, its sub-branch of deep learning (DL) have left the research laboratory and are being applied in real-world applications. The high-tech internet giants, as can be expected, have taken the lead in this field and many businesses are now looking to reap the same benefits. ML can bring automation at scale that manual efforts can neither cope effectively nor even manage at all, creating new business opportunities as well as transforming existing business practices. To build this new generation of applications requires ML development tooling. This report focuses on vendors that offer enterprises a platform for ML development, with solutions that typically offer a lot more in terms of managing the whole development-to-deployment lifecycle.

Omdia view

The roles in building machine learning applications

The key question for this report is who the target reader is. It is an important question because the ML development tool landscape encompasses a huge number of tools, far too many to cover in one Omdia Decision Matrix (ODM). We have therefore chosen the most common need in enterprises today, and to explain this better consider first the three key user roles:

- **Data scientist:** Has skills in statistics and mathematics, ideally to PhD level; has been working with data for many years, may already be responsible for big data within the organization.
- **Data engineer:** Skilled as a software engineer in languages that are used within the ML community and is also able to integrate applications with existing software systems in the organization; is principally focused on big data and ML applications.
- **ML expert:** Most typically skilled to PhD level in ML; will write original ML algorithms, understand and customize popular ML libraries and frameworks, and is an authority on the ML algorithms to use for any given application.

There are other more finely graded roles that dedicate themselves to specific parts of the ML application lifecycle, but the above roles are the key ones (and the role terminology might differ depending on who you speak with, so it is best to consider the actual role description). We may also consider weaker skilled staff that fit in the above definitions with less than PhD level, such as business analysts with domain data knowledge and data wrangling skills who take on data scientist tasks.

To return to the question who the target reader is: it is the data scientist and related weaker forms of that role (less experienced and/or less qualified). To create meaningful ML applications, it is necessary to understand the data that goes into an application, its provenance, how it is pre- and post-processed. It is also necessary to understand the meaning of the application output data and how best to use it. At a minimum, an enterprise needs to have these roles in place to be able to use the platforms covered in this ODM. We talk of platforms rather than tools because these solutions

span the whole ML development lifecycle and typically encompass multiple tools that are ideally accessed from one studio or console environment.

We look to the platform in this ODM to provide automation in ML algorithm (model) selection, training, validation, and testing. It is even better if ML experts are available (it is advisable that a large enterprise serious about ML development should hire them) and they will be able to open the hood and make customizations. Regardless, the idea with these ODM solutions is to enable non-ML experts to produce meaningful ML applications. A use-case scenario in a large enterprise would be setting up a center of excellence in ML development manned by experts in ML across the lifecycle who can provide support to line-of-business departments that will use the platforms covered here. We stress our belief that the minimum qualification to work with these ML platforms is a data expert who understands the business domain and meaning of the data.

Finally, to add some insight into the ML lifecycle tasks that an ML team needs to be involved in and which we look to the ODM platform solutions to support and automate as much as possible, here is an outline:

- **Data wrangling:** Data preparation, extract transform load (ETL) tasks, data cleansing.
- **Feature engineering:** Pre-processing for feeding into ML models, data labeling.
- **Algorithm designing:** ML model creation, design, and selection.
- **Model compilation:** Model building and training options, hyper-parameter optimization.
- **Resource allocation and distributed training:** For large-scale projects use of distributed resources, such as CPUs or GPUs.
- **Results testing and debugging:** Post-processing ML outputs, results evaluation, and rebuild iterations. Champion model selection.
- **Inference resource provisioning:** Deployment into production for ML model in inference mode and suitable resource allocation.
- **Hardware management:** Managing all hardware infrastructure for training and inference modes.
- **Production monitoring:** Monitoring results for any drift, and performance tracking.
- **Retraining:** Data changes with time for multiple reasons and models need to be updated.

The ML development platforms that enterprises should consider

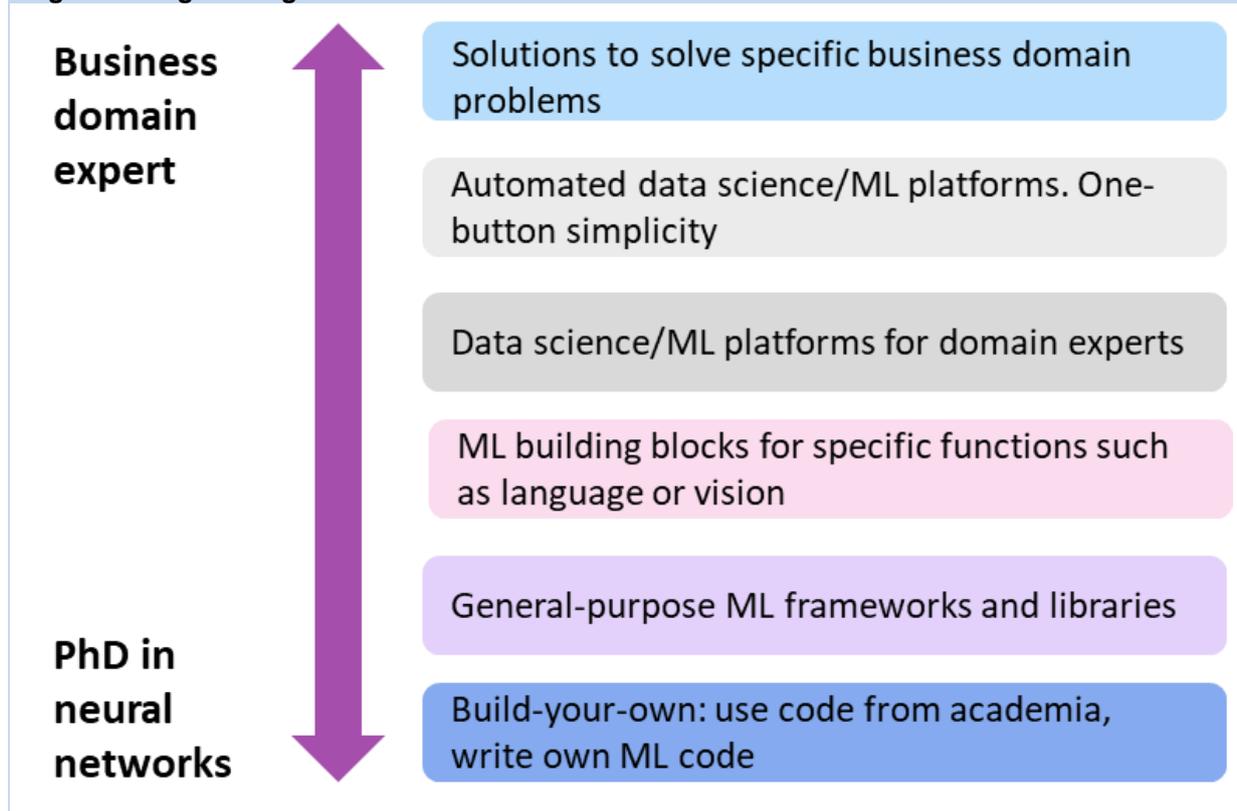
The market for ML application development tools has grown significantly with the rise in popularity of AI, driven largely by the success of DL. The market can be segmented by the level of ML skills required to operate the tool. With reference to Figure 1, these tools can be described as follows, starting from the bottom:

- **Build your own:** For researchers that want to try out novel ideas at the core algorithm level, it is a question of writing your own code and/or trying ideas from code shared by academics. You need a PhD in neural networks to build code at this level and you will need other tools to create the UI.
- **General-purpose ML frameworks and libraries:** This area has exploded with many active projects. Currently most popular is TensorFlow (see Figure 2), the right-hand column shows the ranking, normalized to TensorFlow at 100%.

- **ML building blocks:** Examples are AWS and Microsoft Azure, also Oracle and Salesforce. They offer ML-based, ready-built solutions to be dropped into applications for natural language processing and vision, for example. In some cases, the building blocks allow tuning to the application domain, such as a voice-controlled virtual assistant to a business process.
- **Data science/ML platforms for business domain experts:** These tools let application developers with domain expertise build ML solutions without needing expertise in the algorithm specifics. They do however need to understand the ML lifecycle, how to train the ML model, and how to deploy it.
- **Automated data science/ML platforms:** Greater simplicity through automation with one-button operation to create ML solutions will do the complete data science/ML lifecycle in one swoop. The user performs some experimentation to discover the best solution.
- **Ready-built ML solutions:** Complete out-of-the box solutions that require no building or development by the user and are specific to one application domain.

This ODM reviews products that fit the top three tiers in Figure 1. These tools often have the popular open source ML tools available within the platform; the better tools have these libraries curated, optimized, and managed by the vendor for the platform rather than just be able to read in external models. The AI open source community is highly active and tools such as TensorFlow, PyTorch, Apache MXNet, SciKit, Keras, and others have a high degree of innovation and evolution that vendors find pointless to try to replicate. However, several vendors in this ODM conduct their own in-house ML research (and increasingly contribute back to the open source community), and therefore augment existing open source libraries with their own algorithms within their platforms.

The key benefit of using the platforms covered in this ODM is that it makes working with ML a lot easier for enterprises. The DIY approach is not just a question of knocking out a model in TensorFlow, because there are a host of additional tools to integrate at every stage of the ML lifecycle. The pain of this effort, as well as keeping everything secured, governed, auditable, versioned, and updated becomes a significant effort for an enterprise with hundreds or thousands of ML applications to deploy. These ML development platforms are therefore a must-have for any enterprise serious about deploying ML applications in production and enterprises that have moved beyond experiments in the lab.

Figure 1: Segmenting the ML tools market

Source: Omdia

Key findings

- The market has moved toward ML platforms that work on top of the popular open source ML frameworks and provide a high degree of automation (no-code/low-code citizen developer environments), often described as AutoML. All the vendors in this report except one support open source libraries.
- The large public cloud providers are conducting in-house ML research and augmenting the open source libraries supported in their platforms with algorithms from their research.
- The platforms we have selected in this ODM go beyond development and span the whole ML lifecycle, including operations in production that some call MLOps, not to be confused with AIOps, which is why MLOps is not universally accepted as a term.
- The market will continue to evolve in this highly commercial segment of tooling because it satisfies the demand from enterprises to bring ML applications into production and at scale. We expect to see more automation features in data preparation, which is the most time-consuming phase of the ML application lifecycle, as well as continued innovation in automating ML development.
- The ODM platforms have noticeable offerings in “explainable AI”, such as evaluating which inputs are relevant to the results and testing against bias. Some platforms tackle this topic by selecting at the start ML models that are transparent by nature, excluding neural networks because these are largely black boxes. For legal reasons some ML use cases require results

to be repeatable and transparent to interpretation, determining the class of ML algorithms to be used.

- Talking to all the vendors in this report about their customer use cases, it is clear ML is and will remain an ingredient of real-world applications across all industries. For anyone outside the ML industry, these facts on the ground are not well known and questions abound about whether we are entering another “AI winter”, indicating the extent of confusion about real-world ML and research into general AI. This report hopes to clarify any doubts about real-world use of ML.
- There is applicability of concepts, methods, and tools from software engineering to the ML application development lifecycle, and the use of DevOps-style pipelines to deploy ML applications is a good example of this. Another closely related transfer between these domains is the adoption of cloud-native computing technology (containers to ship out ML applications).

Market and solution analysis

Omdia Decision Matrix: Enterprise ML Development Platforms, 2020–21

Looking at the sector that we described for this report (the top three layers in Figure 1) the ML market has exploded in recent years with four types of players offering a high degree of automation in data science and ML development, with the example vendors covered in this report indicated:

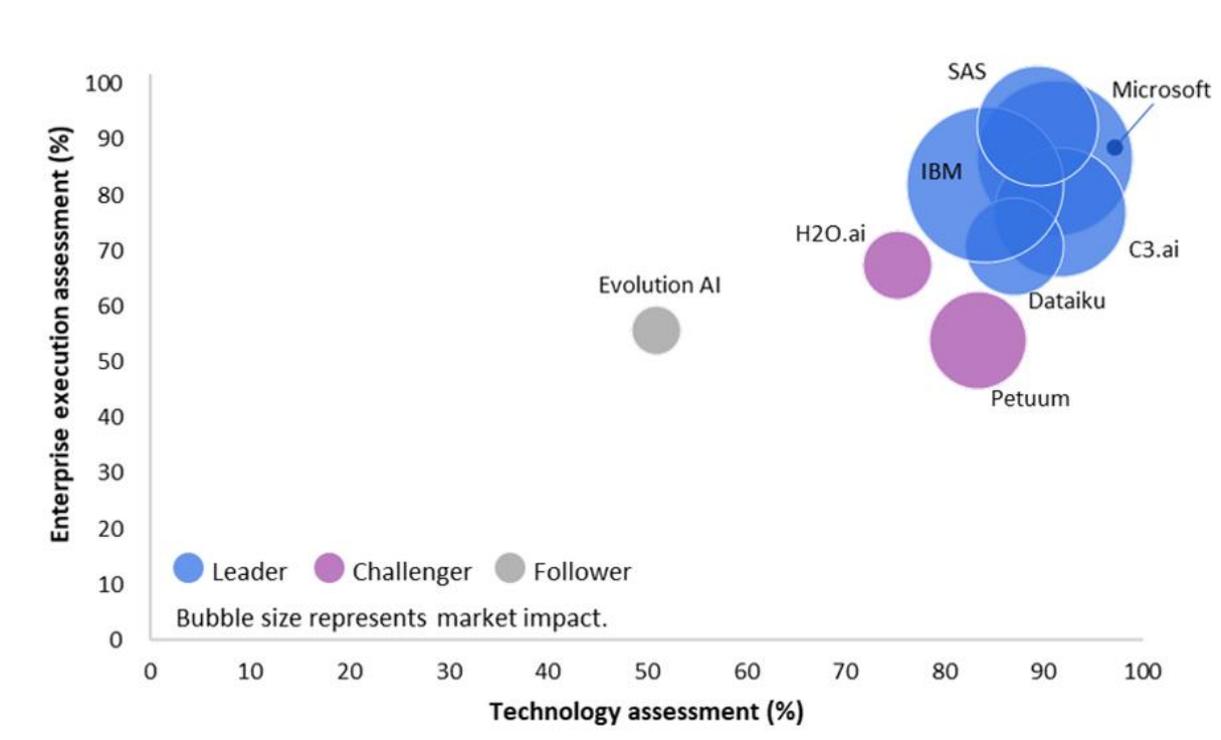
- **Public cloud giant:** IBM, Microsoft.
- **Long established analytics and ML vendor:** SAS.
- **Relatively new ML vendor for general development:** C3.ai, Dataiku, H2O.ai, Petuum.
- **Relatively new ML vendor dedicated to one task:** Evolution AI.

Even with our automation focus, this report is not exhaustive, but it should provide a starting point for shortlisting vendors for further evaluation and proof-of-concept trials.

All the platforms covered in this report provide support for the full ML lifecycle. This can be confusing when evaluating the broader market that has a category of ML lifecycle tools that span the same phases but differ in their emphasis. The best way to make sense of this confusion is to consider how much automation is required. If an enterprise has a team of ML experts building cutting-edge ML algorithms, then their needs will differ from say a bus company that wants to build an intelligent app for installing in each of its buses so that passengers waiting at bus stops have an accurate time of arrival and for which off-the-shelf ML algorithms are fine. The bus company can happily use the products covered in this ODM and have a one-stop platform to work with, automating away much of the complexity involved. Enterprise ML teams that have a far more hands-on approach with algorithm-building skills might want a mix of tools, but even they will find the ODM platforms here useful to kick-start their projects and take much of the drudge out of ML development.

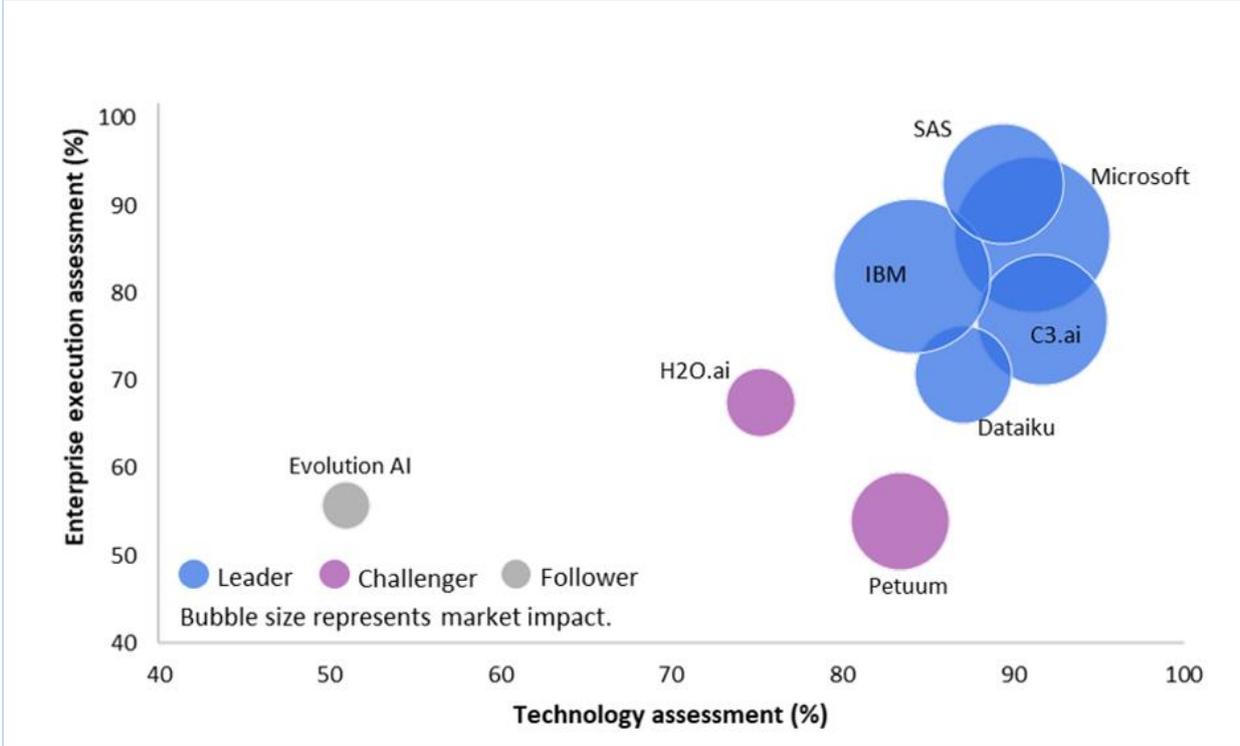
Insight into the criteria used to evaluate the vendor solutions are given in the appendix. The results of our evaluation are shown in Figures 2 and 3 and we have ranked our key vendors into three key groups: Leader, Challenger and Follower (see the Appendix for our definitions of these terms).

Figure 2: Omdia Decision Matrix: enterprise ML development platforms 2020–21



Source: Omdia

Figure 3: Expanded view of Omdia Decision Matrix: enterprise ML development platforms 2020-21



Source: Omdia

Table 1: Omdia Decision Matrix rankings: enterprise ML development platforms 2020–21

Market Leaders	Market Challengers	Market Followers
C3.ai	H2O.ai	Evolution AI
Dataiku	Petuum	
IBM		
Microsoft		
SAS		

Source: Omdia

Vendor solutions

Rankings

In this ODM we have ranked five Leaders (see Table 1). Both the public cloud vendors (IBM and Microsoft) are rated Leaders because they conduct significant research in-house into AI and offer in their platforms the fruits of this research as well as popular ML open source frameworks and libraries. The Leaders, C3.ai and Dataiku, are focused on large enterprise customers across a range of industries. C3.ai has a history of activity in the energy market and has broadened out to other verticals. Both provide an enterprise management and automation layer that sits on top of the most popular open source ML frameworks. Leader SAS has a long history in the analytics and numerical analysis market and has in recent years advanced its capability in AI and ML to become a leader in this space.

The market Challengers are H2O.ai and Petuum. H2O.ai is a major player in the ML open source market and has most recently added new enterprise management and automation tools to work on top of the popular H2O open source offering, which in turn provides curated open source libraries such as TensorFlow and PyTorch. Petuum also provides enterprise management and automation on top of open source ML algorithms and has strengths in distributed out-of-the-box ML.

There is one market Follower in our evaluation: Evolution AI. This vendor only provides tools for extracting information from office documents and suffered in our evaluation due to lacking general-purpose ML application development. However, for the task it focuses on it is an excellent choice and has unique in-house technology.

Technology

The technology evaluation, represented as the x-axis score in Figures 2 and 3, covers the whole of the ML lifecycle: data science; ML development, deployment, performance, scalability, and production monitoring; security; and integration. We looked for features and explanations about how the vendor performs certain tasks.

Apart from the outlier, Evolution AI, the rest of the solutions have close similarities in making use of or being able to consume ML models from the open source frameworks and libraries. Of these vendors, IBM, Microsoft, and SAS conduct in-house ML research and can also therefore offer their own unique ML algorithms. The trend is clearly toward greater automation in all these ODM platforms, because this is where the enterprise demand is high.

There is also a trend toward greater automation in the data science phase (ETL and data wrangling), such as automatic labeling of data for training supervised ML models. We expect to see more automation in this phase of the ML lifecycle.

The final evolution we see in the ODM platforms is around what some call MLOps (not an ideal label because of similarity with AIOps that is more about use of ML predictions in performance of software applications in production), including managing the development and deployment phases of the ML lifecycle, and ensuring ML projects are governed, auditable, version controlled, and access controlled.

Enterprise execution

This dimension of the ODM (the y-axis in Figures 2 and 3) represents how well the vendor is marketing its message and supporting its customers, such as with forums, events, and training. We examine how extensive the partner and system integrator network is. We also look at geographical reach, support for foreign languages, and the rate of business growth.

An important element of the enterprise execution is the availability of business starters and vertical accelerators, as well as pre-built ML services and/or applications to help customers get to speed.

Market impact

The third dimension of the ODM (the circle size in Figures 2 and 3) is a normalized metric for the revenue earnings of the vendor. We normalize to the highest earning vendor and create the circles in an approximate manner to provide representative comparisons.

Vendors not in this report

Broadly speaking, there are just too many vendors to mention, but for the slice of the market that we are focused on, we believe we have included the key players in this report. However, there are two

vendors that offer novel approaches to the focus of this report. Splice Machine, which has an in-database ML solution for bringing ML to RDBMS applications and data repositories, and dotData, which apart from offering a complete end-to-end ML lifecycle development platform, has introduced novel technology in automating feature engineering. Both these vendors appeared on our radar too late for consideration in this report.

Vendor analysis

Microsoft (Omdia recommendation: Leader)

Product: Azure Machine Learning

Availability: Microsoft Azure cloud service

Introduction

Microsoft has seen a change across its customer base, moving from building ML applications to wanting more support in operationalizing these applications in production. For this reason, Microsoft has added MLOps capability to Azure Machine Learning. It has customers deploying thousands of ML applications in the field, such as predicting wait time for a bus, running in each bus in a Toronto bus network.

Microsoft Azure Cognitive Services has pre-built ML models for different scenarios, such as vision, speech, language, web search, and decision that anyone can access and modify (using transfer learning). For example, the decision model is used for personalized recommendations. The decision model is an example of using Microsoft's reinforcement learning (RL) algorithm. RL has been around since the 1990s but it is increasingly being used in production. Microsoft AI research group also has an Autonomous Systems group that is working with customers applying RL in industrial applications spanning energy, process control and automation, manufacturing, and smart buildings. The work from this group feeds into Azure ML. There are additional Microsoft research innovations that feed through into other pre-built ML services, and Microsoft is increasingly open sourcing these innovations to help move the AI community forward. In this last respect Microsoft has made a substantial investment in the OpenAI organization.

Microsoft Azure ML is designed to service both experts in data science and ML as well as those starting out, with a range of tools and options that serve multiple roles and skill sets. Even experts in the field like to use the ease-of-use tool features to help kick-start projects. The Azure ML Studio (classic) consolidates all the tools in one environment and the ML experimental lifecycle is supported with model management, collaboration, and version control, making use of Microsoft-owned GitHub. A new feature to be previewed in March 2020 is the Differential Privacy toolkit (to be open sourced), for ensuring PII data is protected and ensuring it cannot be ascertained by reverse engineering. Also, on the roadmap is a data-labeling service, and a serverless inferencing service that can automatically scale Azure infrastructure to workload demands.

We look at two Microsoft Azure ML use cases. First, internally in Microsoft's customer contact center, Azure ML provides text-based analytics to call center agents for three scenarios: the agent assist bot helps agents in real time, while the real-time supervisor dashboard identifies problem calls so that supervisors can assist the agents, and for post-call analytics the agents use the Interaction Analytics

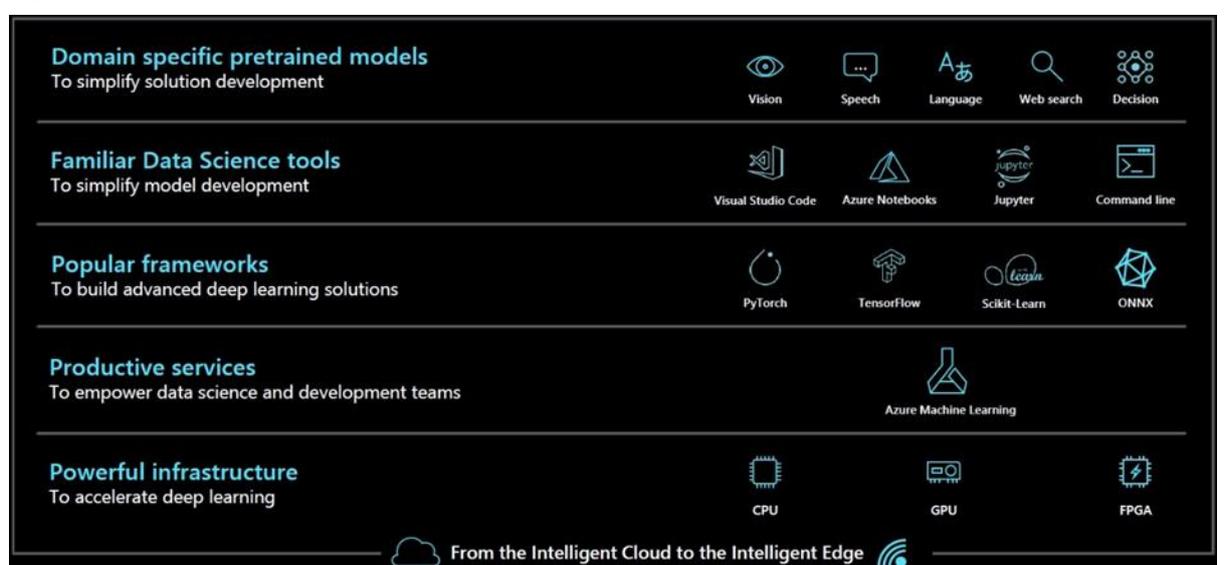
Platform to search call transcripts for specific phrases. As part of the call lifecycle, Microsoft Azure Cognitive Services makes use of language understanding intelligent service (LUIS). This technology works with Genesys call center equipment and Microsoft Teams.

A second customer example is Boots (Walgreens Boots Alliance) pharmacy in the UK, that wanted to know customer preferences across its 2,485 UK stores, 14 million card-carrying customers, and 312 product categories. With data scientists a scarce resource compared with developers, Microsoft Azure Machine Learning automated ML services were used by developers to build ML applications and reduce the backlog of campaign demands building up due to lack of resources. In automated mode the platform will select all available models in parallel trials and select the best performing (terminating runs that are evidently underperforming). It also includes a VotingEnsemble algorithm for combining models.

A host of metrics are provided that characterize the results and enable data scientists to inspect and validate the results, including precision recall, calibration curve, gain curve, ROC, lift curve, and confusion matrix. Without understanding these metrics, developers can simply proceed with the best performing model. However, this is where a governance process is advised to be implemented where an expert double checks the models that eventually go into production, especially where the application has important consequences. All the models are tracked in a registry, and it can be seen which type of models are better suited to the type of applications being developed, helping develop ML skills. The whole process of development is captured in a Jupyter Notebook so that data scientists can inspect and validate the work done and non-experts can reuse the process.

Azure ML explainability features analyze inputs to identify the most influential factors that affect the output. Using Azure pipelines, the model can be deployed across all the different Boots stores, simply connecting with different data sources unique to an individual store. Azure MLOps is then used to monitor and track all the models and advise on possible drift and the need for retraining. MLOps integrates with Azure DevOps to automatically retrain models as and when necessary according to set monitoring rules. This enables large-scale enterprise deployments such as that used at Boots. Microsoft also supports Kubernetes clusters, whether Azure or customers' own.

Figure 7: Microsoft Azure ML



Source: Microsoft

Omdia Strength and Weakness Assessment

Strengths

- ML model creation is a complex task requiring skills that are scarce in the market, so enterprises are looking for tools to automate it. Microsoft's Automated ML fulfills this task by releasing data scientists to focus on the data input and output and deploying the application. Azure Machine Learning automated ML service enables enterprises to scale out their use of ML.
- Microsoft Azure has AI hardware accelerators for both training and inference modes: GPUs are often used for the former and FPGAs for the latter. FPGAs in inference mode have a low latency as well as low power consumption, making them fast in production and helping to reduce costs over time. FPGAs are also reconfigurable, so changing requirements can easily be accommodated.
- With Microsoft's deep heritage in software development it has brought DevOps continuous delivery to the task of deploying ML applications into production and monitoring operations in an activity often called MLOps. For example, Azure ML pipelines define workflows based on DevOps principles, governance data is captured across the full ML lifecycle, and once in production model outputs are monitored for drift.

Weaknesses

- Microsoft Azure is a public cloud, and its ML services are linked to this cloud. While this is not a weakness it does lock in the user to Azure, especially where Microsoft specific services are used. This is not an issue for customers already using Azure for their cloud, and large enterprises typically use more than one cloud.
- Microsoft provides data science and ML team collaboration support for tools on its platform (Teams, GitHub) but could improve the range of collaboration support for popular third-party tools. Organizations are increasingly turning to collaboration tools that go beyond emails and help retain knowledge within projects.
- The range of development languages supported on Azure ML, Python, and R, represent the most popular data science and ML languages, but there are other languages in enterprise use. For example, Scala, as a JVM language, is a skill found in enterprises, and compared with its peers Microsoft might want to extend the range supported.

Appendix

Vendor solution selection

Inclusion criteria

This ODM required vendors to offer a ML development platform targeting enterprises wanting to build their own ML applications. We invited the leading players to participate, able to demonstrate in their platforms data science, ML development and end-to-end ML lifecycle technology features.

Given the wide spectrum of tools available in the market, our focus was on a platform that primarily supported the data scientist and automated as much of the ML build, train, and deploy as possible. A

prerequisite for these platforms is a user expert in the business domain data (these platforms are not designed for unskilled users).

In summary, are key inclusion criteria are:

- Vendor has an offering fitting an enterprise ML development platform. Platform should have a degree of automation and ease of use for non-ML experts.
- There are two categories of vendor that are considered for inclusion in this evaluation: the vendor must have significant market share relative to peers and is either a recognized leader in the market or has the potential to become one, or the vendor is a niche player or an emerging player with outstanding market leading technology.

Exclusion criteria

The ODM is not designed to exhaustively cover all the players in a market but a representative set of the leading players. Omdia also invites smaller, possibly niche, vendors that have innovative solutions and are on a fast growth path. With this flexibility we consider each participant on its merits as a good fit to the ODM topic.

This ODM excludes vendor solutions that are complete ML solutions out-of-the-box ready for use in vertical application domains. The project also excludes solutions not targeting enterprises. Finally, the project excludes solutions that are essentially a collection point for open source tools but with little integration and easy-to-use automation offered.

Methodology

- Vendors complete a comprehensive capability questionnaire in a spreadsheet, covering the three dimensions of the ODM and these are scored to produce the ODM chart.
- There is a series of comprehensive, structured briefings with all key vendors, including a demonstration where possible.
- Supplemental information is obtained from vendor literature and websites and from the results of Omdia surveys.
- The report is peer reviewed by Omdia analysts.

Definition of the ODM

The ODM spans three assessment dimensions.

Technology

In this assessment dimension, Omdia analysts develop a series of features and functionality that provide differentiation between the leading solutions in the marketplace.

Market execution

In this dimension, Omdia analysts review the capability of the solution around key areas such as: enterprise fit, business vision and innovation, interoperability, language support, product roadmap, business starters, and partner ecosystem.

Market impact

The global market impact of a solution is assessed in this dimension. Market impact is a metric normalized to the market leader and is mainly based on the solution's global revenue.

Omdia ratings

- **Market leader.** This category represents the leading solutions that Omdia believes are worthy of a place on most technology selection short lists. The vendor has established a commanding market position with a product that is widely accepted as best of breed.
- **Market challenger.** The solutions in this category have a good market positioning, and the vendors are selling and marketing the product well. The products offer competitive functionality and good price-performance proposition and should be considered as part of the technology selection.
- **Market follower.** Solutions in this category are typically aimed at meeting the requirements of a narrower range of customers. A niche or relatively new vendor with strong innovative may fall into this category and should be explored as part of the technology selection.

Further reading

2020 Trends to Watch: Artificial Intelligence, INT002-000270, February 2020.

Deep Learning, DL-18 Tractica, 4Q 2018.

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Omdia Consulting

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