



Automated Machine Learning (Auto ML) in Network and Service Management: Overview and Significance

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Abstract: Automated Machine Learning (Auto ML) is transforming network and service management by making it easier to apply machine learning methods to intricate network settings. In order to facilitate quicker deployment and more effective network operations, auto ML platforms automate a number of machine learning workflow processes, including as data pretreatment, model selection, and hyperparameter customization.

INTRODUCTION

Increasingly complex and dynamic networks and services necessitate clever and effective management solutions. With the ability to perform “zero-touch” procedures, Automated Machine Learning (Auto ML) has become a very promising technology that could be completely change network and service administrations. Utilizing Artificial Intelligence (AI) and Machine Learning (ML), Auto ML streamlines network and service configuration design, deployment, and optimization, resulting in increased efficiency, decreased down time, and better user experiences. The main emphasis lies in the utilization of Auto ML within the framework of 5G, 6G, and additional cutting-edge technologies. Among the many topics covered in this session is the application of Auto ML to automate network and service configuration creation, deployment, and optimization, leading to increased efficiency, less downtime, and improved.

How is Auto ML implemented

Try automatic machine learning training by following these steps:

- Determine whether Machine Learning (ML) has to be applied to computer vision, NLP, regression, forecasting, or classification.
- Select the web experience of the no-code studio is to be considered. and an experience focused on writing code first.
- The Azure ML SDKv2 and Azure ML CLIv2 are available to users who would rather work with code initially.
- Start using the tutorial here: Learn to use Auto ML and Python to train an object detection model.
- For those who would rather work with less or no code, Azure ML Studio's web interface can be processed at <https://ml.azure.com>.
- Using automated machine learning, create a categorization model in Azure ML.

Name The origin of the instruction set with labels: There are numerous methods that you may integrate your data with Azure Machine Learning.

IMPORTANT TERMINOLOGY AUTOML

1) Natural Language Processing

Models for text categorization and named entity training using text data identification situations can be generated with ease thanks to automated machine learning (ML) assistance with tasks related to natural language processing (NLP). The Azure ML Python SDK facilitates the creation of automated ML-trained NLP models. One can access the models, outputs and experimentation jobs that come from this process through the Azure Ma studio UI.

The NLP capacity facilitates

Using the most recent pre-trained BERT models, complete deep neural network natural language processing training smooth data labeling integration with Azure Machine Learning Utilize tagged data to create NLP models.



2) Regression

Resembling classification tasks, regression tasks are also frequently used in supervised learning. Regression-specific feature sets are available through Machine Learning. Discover other possibilities for featurization. Supported algorithms is another place where you may obtain a list of the algorithms that AutoML supports.

In contrast to classification models, which numerical results derived from regression using independent predictors models forecast numerical output values depending on category. Regression analysis uses an estimate of the influence of one variable on the others to assist determine the link between those independent predictor variables. In light of variables like safety rating and gas mileage, for instance, the model might forecast the cost of an automobile.

These Python notebooks provide an example of automated computing and regression for forecasts. Hardware Effectiveness.

3) Time-Series Forecasting

Creating predictions is a critical component of any organization, regardless of sales, inventory, revenue, or client demand. Automated machine learning (ML) can be used to integrate methods and strategies and provide a time-series forecast that is highly recommended. The list of algorithms that AutoML supports is available under Supported Algorithms.

A multivariate regression problem is applied to an automated time-series experiment. Values from previous The temporal sequence is "pivoted" to add extra dimensions to the inverse in addition to existing predictors. This method has the advantage of organically including various contextual variables and their interaction during training, which is not the case with classical time-series methods. For every item in the dataset and every prediction horizon, automated machine learning (ML) develops a single, but frequently internally branching, model. So, there is more data accessible to determine the model's parameters.

Configuration for advanced forecasting consists of:

- ✓ Identification and feature-rich holiday content
- ✓ Auto-ARIMA, Prophet, ForecastTCN, and DNN learners using time series
- ✓ Grouping is a common way for many models to provide
- ✓ Cross-validation based on rolling origins
- ✓ Modifiable latency
- ✓ Rolling window aggregate characteristics

CLASSIFICATION

In supervised learning, models that are trained on training data can apply their newly acquired knowledge to fresh data through the process of classification. Particularly designed for these kinds of jobs, Azure Machine Learning provides featurizers including deep neural network text featurizers for categorization. See Data featurization to learn more about your options for featurization. Supported algorithms is where Additionally, a list of algorithms is available in AutoML.

Predicting which classifies fresh data will be categorized based on insights from instruction data is the primary objective of categorization algorithms. Examples of common classifications are object detection, handwriting recognition, and fraud detection.

This Python notebook provides an example of automated machine learning and classification: Financial Marketing.

Using AutoML to Promote additionally Enhancing Research

Encouraging a science of finding models contends that the effectiveness of a particular method relies on both the basic algorithmic quality and the finer points of its tuning, and that it can occasionally be challenging to determine whether a method is indeed superior or just better tuned. Bergstra and colleagues suggested using the same hyper parameter optimization toolbox to tune all algorithms, leading to better reporting outcomes. It provides instances from recent



work showing improvements in proper hyperparameter baseline optimization over the most recent cutting-edge findings as well as suggestive techniques.

The process of fine-tuning hyperparameters for novel jobs can be automated by hyperparameter optimization and algorithm configuration, which diminish effort, time, and human error.

Features of the AutoML tool

- 1) The cloud-based automated machine learning platform developed by Google is called Google AutoML.
- 2) Cloud-based, proprietary platform called Azure Automated Machine Learning.
The Texas A&M Data Lab created the open-source software library AutoKeras.
- 3) A commercially available, open-source set of basic Python machine learning tools called Scikit-learn gave way to Auto-sklearn.

Various Applications of AutoML

- In the field of finance, fraud detection is enhanced by this technique, making models more accurate and precise.
- Large-scale data analysis and insight-drawing are possible with research and development in the healthcare industry.
- For facial recognition, image recognition is helpful.
- Banking, finance, and insurance all involve risk assessment and management.
Risk assessment, monitoring, and testing can be done with cybersecurity.
It can be applied to customer service to improve team productivity and analyze sentiment in chatbots.
- In order to create adaptable cyberthreats, malware and spam might be employed.
Utilizing it in agriculture helps speed up the process of quality testing.
Behavioral marketing initiatives on social media can be made more effective by using predictive analytics in marketing.

Why Do We Need AutoML Solutions?

- A collection of techniques and algorithms known as "AutoML" (automatic machine learning) make it simpler to integrate machine learning with particular problems.
- Through the automation of several processes required within creating and developing a model for machine learning, autoML solutions aim to make the technology more accessible to those who are not machine learning experts.
- This can involve actions like preprocessing the data, fine-tuning the model's hyperparameters, and choosing the best machine learning algorithm for a particular application.
- Models for machine learning that may be utilized variety of purposes, including fraud detection, supply chain efficiency improvement, and customer behavior prediction, can be built with the aid of autoML solutions.

IMPORTANT THINGS TO CONSIDER WHEN SELECTING AN AUTOML SOLUTION

1) Cloud vs Augmented

AutoML solutions for augmented reality are made to integrate with your current machine learning infrastructure, such on-site hardware or your data center.

They usually offer a number of features and tools that may be utilized to make machine learning automated process, but still in charge of infrastructure management and upkeep. Conversely, cloud-based AutoML solutions are controlled by the provider and are housed in the cloud. This relieves you of the burden of overseeing and upkeep of the infrastructure, but it can also give you fewer restrictions on the underlying technology and its application.

2) Cost

While some solutions are open source or free, others could be commercial and call for a license or subscription cost. When selecting an AutoML solution, take your budget into account as well as the value the solution offers.

3) Assistance and Records

While several systems might offer more comprehensive records and assistance, others might just offer a restricted range of help choices. Selecting an AutoML solution should take your needs and desired level of support into account.



4) Cloud versus Augmented

Solutions for augmented autoML are made for integrate alongside our infrastructure for machine learning as it stands now, like hardware that is on-site or in your data center. You are in charge of overseeing and maintaining the infrastructure, but they usually offer a variety of features and tools that can be utilized to to streamline the procedure for machine learning. On the other hand, cloud-based AutoML solutions are hosted on the cloud and are usually under provider management. You might be less in charge of the underlying technology and its application. utilized, but you won't must be concerned with overseeing and repairing the infrastructure.

5) Self-constructed versus Corporate

It possesses knowledge and materials necessary for develop using your own AutoML program, you might possess the ability to produce a product that is customized to meet your unique demands. But, you might want to think about utilizing a commercial solution if you lack the knowledge or resources to create your own AutoML program. Commercial AutoML solutions are generally created by machine learning specialists with a team of professionals that can assist with setup and ongoing maintenance.

BEST AUTOML WORKSPACES

1) Azure AutoML

Microsoft offers Azure AutoML, a set of automated machine learning tools and services, as a component of the cloud computing platform Azure. Its goal is to simplify the process for companies and groups creating and implementing unique machine learning models. For time series forecasting and supervised learning, Azure AutoML is helpful.

2) Amazon Lexual

AWS's Amazon Lex service enables programmers to create text-and voice-based conversational user interfaces for applications. It makes it simple for developers to construct chatbots and other interfaces that can be linked with websites, mobile apps, and messaging platforms. It is built using the same technology as Alexa, a virtual assistant from Amazon.

With the help of Amazon Lex's many features and functionalities, including its natural language comprehension and automated speech recognition, developers can fastly and simply design complex user interfaces for a variety of uses, including eCommerce, customer service, and information collecting.

3) H2O AutoML

Majority of the processes applied in creating and refining models for machine learning, including data pretreatment, algorithm selection, and hyperparameter optimization, are automated by H2O AutoML. H2O AutoML is a component of the larger H2O.ai platform that provides a number of services and tools for using artificial intelligence and machine learning on a variety of activities.

4) Auto-Keras

On the well-known Keras deep learning library, Auto-Keras is built. It is intended to be user-friendly, even for non-machine learning experts. It can be applied to grouping, regression, and classification tasks. With just a few lines of code, its high-level APIs—such as Text Classifier and Image Classifier—can assist in solving machine learning challenges. It also offers the basic components needed to conduct an architecture search.

5) ML box

Machine learning can be automated in in tandem with an open-source program library called MLBox. It is made to help people create and train machine learning models more easily, without requiring a high level of technical knowledge. Python is the programming language used to write it.

Superior machine learning models for a variety of apps can be rapidly and simply constructed by users with the aid of MLBox's many features and capabilities, which include model selection, automatic feature engineering, and hyperparameter tuning. Uses for MLBox include clustering, regression, and classification. It is licensed under the BSD3 license.

AUTO-SKLEARN

An open-source software library called Auto-SKLearn uses the Python programming language to automate the process of creating and choosing machine learning models.



With its foundation in the well-liked scikit-learn machine learning library, its goal is to simplify the process of applying machine learning to users' data without necessitating a deep understanding of the underlying methods and algorithms.

High-quality machine learning models can be swiftly and simply constructed by users with the aid of Auto-SKLearn's many characteristics and talents, which include selecting models automatically and optimizing hyperparameters. Predictive modeling, classification, and clustering are just a few of the many uses for Auto-SKLearn, which is licensed under the BSD3 license.

1) Google Cloud AutoML

To help businesses applying the machine learning to particular performance like language translation, image and recognition and natural language processing AutoML offers a suite of tools and services called AutoML Vision, AutoML Natural Language, and AutoML Translation.

Reinforcement learning, a branch of machine learning that uses procedure to let a system learning from its surroundings by coordinating with it and getting feedback, is what Google used to develop these tools.

2) Run: ai

A proprietary software called Run: ai is used to automate machine learning infrastructure. The platform provides workload orchestration for your whole machine learning infrastructure in addition to controls for automated resource management in terms of Auto ML.

Run: ai allows you to configure GPU quotas, pool GPU compute resources, and dynamically adjust resource allocation. With the help of these features, you can make sure that even the most resource-intensive deep learning models use resources at scale and truly optimize your compute resources.

To whom is Auto ML intended?

Both inexperienced and seasoned AI practitioners can benefit from AutoML. A straightforward wrapper function offered by H2O's AutoML carries out numerous modeling-related operations that would normally need a substantial amount of code. Users gain from this in a number of areas, including:

Financial Services: AutoML technologies help established financial firms and emerging fintechs address obstacles including AML, transaction fraud, trade failures, credit risk lending, and customer attrition.

Government: To enhance fraud, waste, and abuse, supply chain and logistics, internal and external cyber security, and human resources, government organizations are utilizing AI and AutoML to optimize their massive data repositories.

Health: AutoML gives medical practitioners in the public and private sectors optimized data and Finance.

Insurance: By employing AI to close knowledge gaps and enhance automated underwriting, claims processing, precision pricing, customer attrition, and fraud protection, the insurance sector is making effective use of artificial intelligence.

Manufacturing: Top producers forecast demand, anticipate stock levels, maintain machines predictively, forecast returns, and identify faults in their supply chains. These strategies all help them cut expenses and optimize operations. AI and machine learning are used in these processes.

Marketing: Marketing firms and companies utilize AutoML to generate targeted lead generation, upsell and cross-sell promotions, investment opportunities, market projections, ideal ad placement, funnel predictions, and customer segmentation and recommendations.

Telecommunications-To guarantee a constantly-improving customer experience, the telecommunications sector makes extensive use of AI in predictive customer service, fleet management, fraud detection, customer retention, and optimal marketing.



Automated Deep Learning and Architecture Search

The challenge of locating a deep neural network design with optimal performance is tackled by the discipline of architecture search. Because developers do not have to laboriously assess several architectures, automated architectural search can significantly accelerate the development of new deep learning applications.

The following packages are available for deep learning hyperparameter optimization and architecture search:

- Auto-Pytorch
- AutoKeras
- Talos.

Process of Auto ML

The two most useful aspects of AutoML are the automation of the tuning (or hyperparameter optimization) process and the selection of machine learning models. It takes a combination of methods to do this.

The concept of human neurons' ability to react to stimuli and communicate with one another by sending signals is the foundation of one kind of machine learning. We refer to this collection of millions of nodes as a neural network. Nodes can divide large problems into smaller tasks in order to handle them.

To identify whether an object is furry, for instance, a layer of nodes in the neural network responsible for dog recognition may be present. Tails, legs, or color patterns could be sought for by a new layer. With continuous training using hundreds of instances, this intricate system evolves automatically.

Neural networks and its environments

A significant advancement in computers is machine learning. The days of manually processing the massive amount of data gathered from various sources are long gone. It appears nearly impossible and completely ineffectual now. Neural networks, in contrast to standard software systems, can accommodate additional layers without experiencing a rise in complexity.

Neural Architecture Search (NAS) is a collection of techniques used with neural networks and deep learning that forms the foundation of AutoML. After receiving the data set as input, the NAS collection of algorithms determines which architecture and hyperparameters are most pertinent. These algorithms can practically take the position of ML engineers, as the model is automatically adjusted.

Meta-Learning

The capacity of diverse machine learning techniques to function on a variety of dataset types is known as meta-learning, or the "learning to learn." As a result, one becomes more efficient, learns from the results, and completes new jobs far more quickly. Models for machine learning gain knowledge from past data.

Catalyst Zia Models

Without the need for explicit instructions, Catalyst AutoML, a Catalyst Zia Services component, examines a collection of training data and forecasts the result of a specific portion of that data. By giving a dataset, training columns for analysis, and the target column whose value you need to forecast, you can train models in AutoML. After that, Zia trains the model to produce predictive insights using the dataset by iteratively running it through many machine learning methods. Then, you can use AutoML into your predictive analytics-based Catalyst applications.

Through the Catalyst web portal, you may access and configure AutoML for your project. A model can be tested and values can be predicted using the Catalyst console once it has been trained.

Create a Model

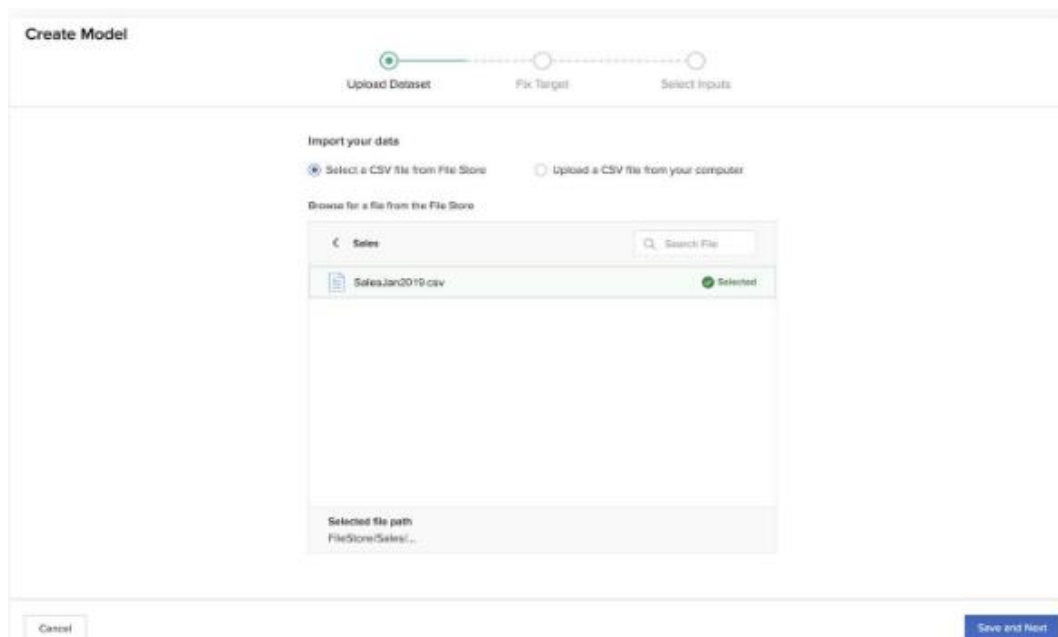
There are few steps involved in constructing and training a model. We'll talk about them sequentially. Using Catalyst, to build and train an Auto ML model

1. Select the Auto ML page and click Create Model.



2. Uploading a dataset is the initial stage. You have two options for importing a dataset: uploading a CSV file from your PC or choosing one from one of your folders in the File Store.

By clicking on the file and heading to its folder, you can choose a CSV file from the File Store.



By searching for it on your computer or dragging it into the drop box, you can upload a CSV file.



Next, you need to save the CSV file to one of your File Store folders. You can either make a new folder or choose an already-existing one.

3. Click "Save" and "Next."

Column Name	Type	Missing	Distinct Values	Mean	SD	Correlation with target
Account_Created	Date	0%	976	—	—	—
Payment_Type	Categorical	0%	4	—	—	—
Name	String	0%	765	—	—	—
Last_Login	Date	0%	977	—	—	—
Transaction_date	Date	0%	987	—	—	—
Latitude	Numerical	0%	706	39	20	—
Country	String	0%	56	—	—	—
Longitude	Numerical	0%	723	-41	67	—
Price	Categorical	0%	9	—	—	—

As was previously mentioned, after you upload a dataset, Zia examines it to identify the type of data in each column of the CSV file. The values in the column are used to determine the data kinds. For instance, Zia identifies a column's data type as binary-class categorical if it contains only two unique values that are repeated throughout all of the records.



Additionally, AutoML computes and shows the values for missing percentages, unique entries for every column, and the mean and standard deviation for numerical columns. A brief summary of a column can be viewed by hovering over its tooltip.

Additional details like the name, total number of columns, and number of records in the dataset are also available on the website.

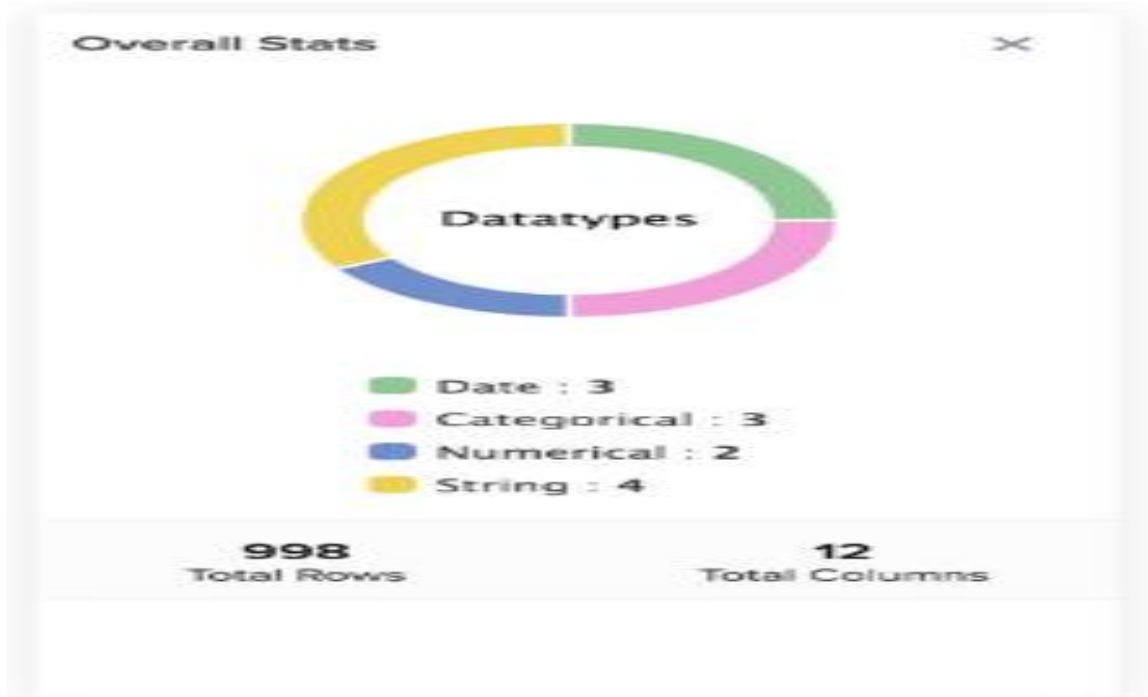
The screenshot shows the 'Create Model' interface with a progress bar at the top containing 'Upload Dataset', 'Fix Target', and 'Select Inputs'. Below the progress bar, there is a 'Target column' section with a dropdown menu open, listing 'Payment_Type', 'Latitude', 'Longitude', 'Price', and 'Product'. Below this is a dataset summary for 'SalesJan2019.csv' with 12 columns and 998 rows. A table lists the columns with their types, missing percentages, and distinct values.

Column Name	Type	Missing	Distinct Values	Mean	St. Dev.	Min	Max
Account_Created	Date	0%	976	—	—	—	—
Payment_Type	Categorical	0%	4	—	—	—	—
Name	String	0%	765	—	—	—	—
Last_Login	Date	0%	977	—	—	—	—
Transaction_date	Date	0%	987	—	—	—	—
Latitude	Numerical	0%	706	39	20	—	—
Country	String	0%	56	—	—	—	—
Longitude	Numerical	0%	723	-81	67	—	—
Price	Categorical	0%	9	—	—	—	—

If Zia made a mistake in its prediction, you can adjust the column's data type. You'll get an error message stating that the update is invalid if the data type you select doesn't match the values in the column. You will get the error warning, for instance, if you choose Date as the data type for a column with entirely numerical value

The screenshot shows a close-up of the 'Type' column in the dataset summary table. A dropdown menu is open for the 'Last_Login' row, showing options: 'String' (checked), 'Numerical', and 'Date'. The 'Date' option is highlighted, indicating it is the selected option.

Column Name	Type	Missing
Account_Created	Date	0%
Payment_Type	Categorical	0%
Name	String	0%
Last_Login	String	0%
Transaction_date	Numerical	0%
Latitude	Numerical	0%



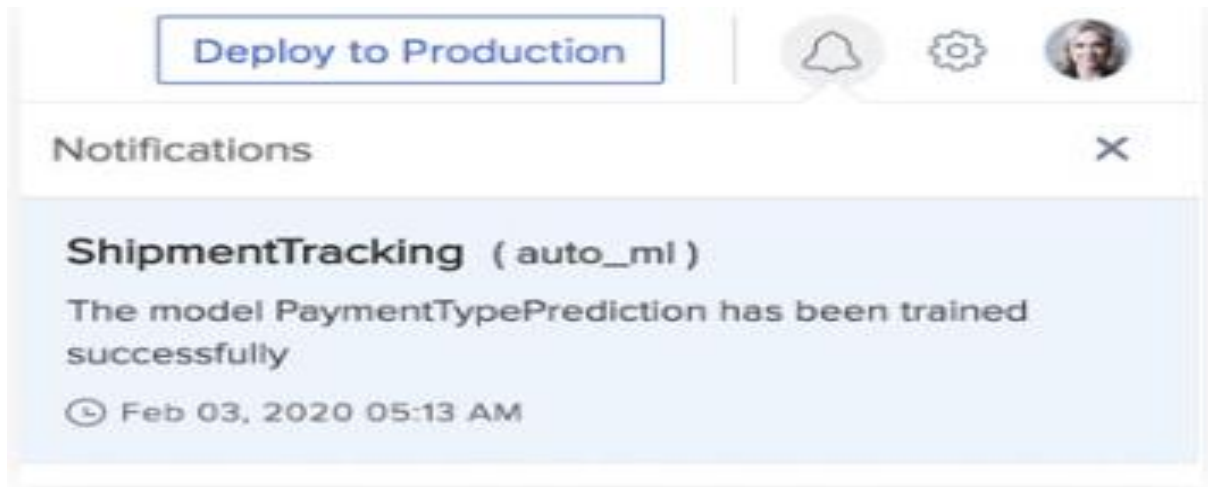
By selecting View Overall Stats on the page, you may also see the dataset's overall statistics in a visual graph.

The image shows a filter configuration interface with the following sections:

- Type**: A dropdown menu with "Date" selected.
- Missing (in %)**: A dropdown menu with "Less than" selected and a text input field containing "5".
- SD**: A dropdown menu with "Greater than" selected and a text input field containing "20".
- Mean**: A dropdown menu with "Greater than or Equal to" selected and a text input field containing "25".
- Correlation (in %)**: No further configuration is visible.

At the bottom, there is a "Clear" button on the left and an "Apply Filters" button on the right.

You will receive a notification in your Catalyst console upon completion of the training informing you of the model's training success or failure.



The model's Evaluation Report and Model Prediction sections are now viewable. At the conclusion of this part, we will talk about these.

The AutoML page lists the generated model. When referring to the model that is utilizing the API, a distinct Model ID is generated for it.

The page also shows information about each model, including its kind, generated date, status, and name of the dataset that goes with it. When a model completes training successfully, it displays the state as Completed. Using the search field, you can look up a model by name.

Model Name	Model ID	Dataset Name	Type	Created Time	Status
CustomerCountPrediction	105000000124001	CustomerDetails.csv	Regression	Feb 07, 2020 02:30 AM	Completed
PaymentTypePrediction	105000000121023	Sales.Jan2019.csv	Multi-Class Classification	Feb 03, 2020 05:13 AM	Completed
DeliveryTypePrediction	105000000120007	ShipmentData.csv	Binary-Class Classification	Jan 27, 2020 02:47 AM	Completed

BIG ML

BigML AutoML's initial version assists in automating not just the model selection process but the entire machine learning pipeline. Furthermore, it is quite easy to utilize. Three primary functions of BigML's AutoML are feature generation, feature selection, and model selection.

BigML enables countless predictive applications in a variety of sectors, such as IoT, healthcare, pharmaceuticals, aerospace, automotive, energy, entertainment, financial services, food, and telecommunications.

AutoML Issues and How to Prevent Them

Initially, analyzing unstructured and semi-structured data is a challenge for AutoML engineers. The second thing to note is that there are changing optimization targets for modern AutoML frameworks. After the final results are revealed, there is only one method for making an informed decision.

Moreover, the rapid changes in the environment make it challenging to apply machine learning models and produce reliable results. The market's available AutoML apps are limited to one machine-learning model program. PyTorch is one example.



An additional obstacle that needs to be addressed is the need for machine learning models to be explainable. It is, to some extent, a matter of individual interpretation. The resulting solution might not align with the end users' anticipated outcomes. Companies must focus on establishing principles concerning comprehensible and reliable machine learning. And lastly, when it comes to the security and privacy of machine learning models, enterprises are facing a lack of standards, legislation, and regulation. Different scenarios should be addressed by modern technical solutions.

We at Forbytes are here to help you overcome each of these obstacles. Are you prepared to use AutoML to grow your company to new heights? Allow us to serve as your guide. To find out how automated machine learning may improve your operations, get in touch with us right now.

Considering AutoML's Future

It is projected that AutoML will play a major role in determining the future course of machine learning as it develops and expands. The ability of AutoML to automate the intricate procedures needed to create machine learning models has the potential to democratize machine learning and promote innovation in a number of industries.

Furthermore, the need for effective, precise, and scalable machine learning solutions is anticipated to increase in tandem with the volume of data that businesses produce, strengthening the position of AutoML in the field of machine learning going forward.

Examining the Specifications of AutoML

Numerous features are included in AutoML systems, all of which are designed to streamline and improve the different components of the machine learning process. The automated pre-processing of data, feature selection, model selection, and hyperparameter tuning are the essential elements of an AutoML system.

Automated Selection of Features

Choosing the most relevant features from a dataset to increase model performance is a critical step in the feature selection process. AutoML platforms can automate this by employing algorithms to determine which features are most relevant and how important they are.

Selecting Models Automatically

Choosing the best model for a given machine learning task is frequently difficult. By analyzing several models and selecting the one that performs the best for the particular job, AutoML streamlines this process.

Autonomous Hyperparameter Adjustment

A machine learning model's hyperparameters must be set up prior to model training because they cannot be learned from data. The overall performance of the model can be improved by automating the optimization of these hyperparameters using autoML techniques.

ONNX & AutoML

You may create a Python model with Azure Machine Learning and have it automatically translated into the ONNX format. Once the models are in the ONNX format, they can be used with a variety of devices and platforms. Study up on using ONNX to speed up machine learning models.

You can use the automatically-built model in your C# apps without recoding or dealing with the network latencies introduced by REST endpoints because the ONNX runtime supports C# as well. Find out more about using the ONNX runtime C# API for inferencing ONNX models and using an AutoML ONNX model in a .NET application with ML.NET.

Summary

Machine learning has advanced significantly with the introduction of autoML, which increases its scalability, efficiency, and accessibility. It is impossible to overestimate the significance of AutoML in creating accurate and trustworthy machine learning models as we move further into the big data age. Anyone interested in harnessing the power of data analysis and interpretation must comprehend the concept, characteristics, advantages, and the consequences of AutoML for the future of machine learning.

CONCLUSION

The integration of Automated Machine Learning (AutoML) in network and service management offers significant benefits in terms of efficiency, scalability, and proactive decision-making. By automating the development and



deployment of machine learning models, organizations can streamline network traffic optimization, enhance fault detection, and improve predictive maintenance processes. This results in a more resilient, adaptive, and efficient network infrastructure, ultimately improving service quality and reducing operational costs. As network systems become increasingly complex, leveraging AutoML allows for faster insights, better resource allocation, and quicker responses to issues, paving the way for smarter and more dynamic network and service management practices.

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