DP100-Azure Data Scientist Associate

Manage data ingestion and preparation, model training and deployment, and machine learning solution monitoring with Python, Azure Machine Learning and MLflow.

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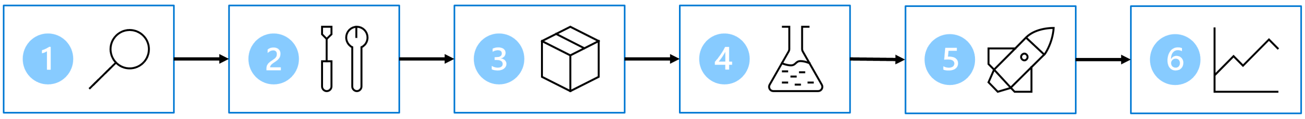
1. Design a machine learning solution

1.1 Design a data ingestion strategy for machine learning projects



Six steps to plan, train, deploy, and monitor the model:

- Define the problem
- Get the data
- Prepare the data
- Train the model
- Integrate the model
- Monitor the model

Three different formats:

- **Tabular or structured data** - *an Excel or CSV file*
- **Semi-structured data** - *JSON object*
- **Unstructured data** - *documents, images, audio, and video files*

1


```
{ "deviceId": 29482, "machine": "Machine1", "time"="2021-07-14T12:47:39Z", "temperature": 20.4 }
{ "deviceId": 38273, "machine": "Machine1", "time"="2021-07-14T12:47:49Z", "temperature": 20.6 }
{ "deviceId": 43819, "machine": "Machine2", "time"="2021-07-14T12:47:33Z", "temperature": 23 }
{ "deviceId": 38273, "machine": "Machine1", "time"="2021-07-14T12:47:54Z", "temperature": 20.4 }
{ "deviceId": 29482, "machine": "Machine1", "time"="2021-07-14T12:48:35Z", "temperature": 20.6 }
{ "deviceId": 58291, "machine": "Machine2", "time"="2021-07-14T12:48:36Z", "temperature": 23 }
```


2

Device ID	Machine	Date	Time	Temperature
29482	Machine1	2021-07-14	12:47:39	20.4
38273	Machine1	2021-07-14	12:47:49	20.6
43819	Machine2	2021-07-14	12:47:33	23
38273	Machine1	2021-07-14	12:47:54	20.6
58291	Machine2	2021-07-14	12:48:36	23

3

Machine	Date	Time	Temperature
Machine1	2021-07-14	12:47	20.5
Machine2	2021-07-14	12:47	23
Machine1	2021-07-14	12:48	20.5
Machine2	2021-07-14	12:48	23

Three common options for storing data:

- **Azure Blob Storage** - Cheapest option for storing data as unstructured data. Ideal for storing files like images, text, and JSON.
- **Azure Data Lake Storage (Gen 2)** - *advanced version of the Azure Blob Storage*. Also stores files like CSV files and images as unstructured data. *Storage capacity is virtually limitless so ideal for storing large data.*
- **Azure SQL Database** - Stores data as structured data. *Ideal for data that doesn't change over time.*

To create a data ingestion pipeline:

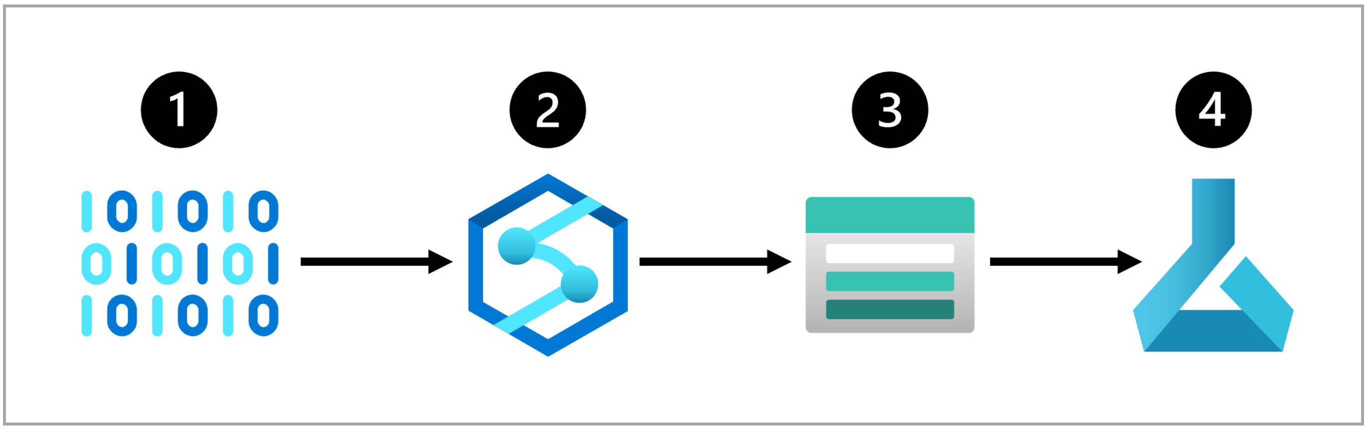
- **Azure Synapse Analytics** - create and run pipelines for data ingestion.
- **Azure Databricks** - uses Spark clusters, which distribute the compute to transform large amounts of data in less time.
- **Azure Machine Learning** - provides compute clusters, which automatically scale up and down when needed.

> ***Data transformations may perform better when you execute them with either Azure Synapse Analytics or Azure Databricks instead of using Azure Machine Learning.***

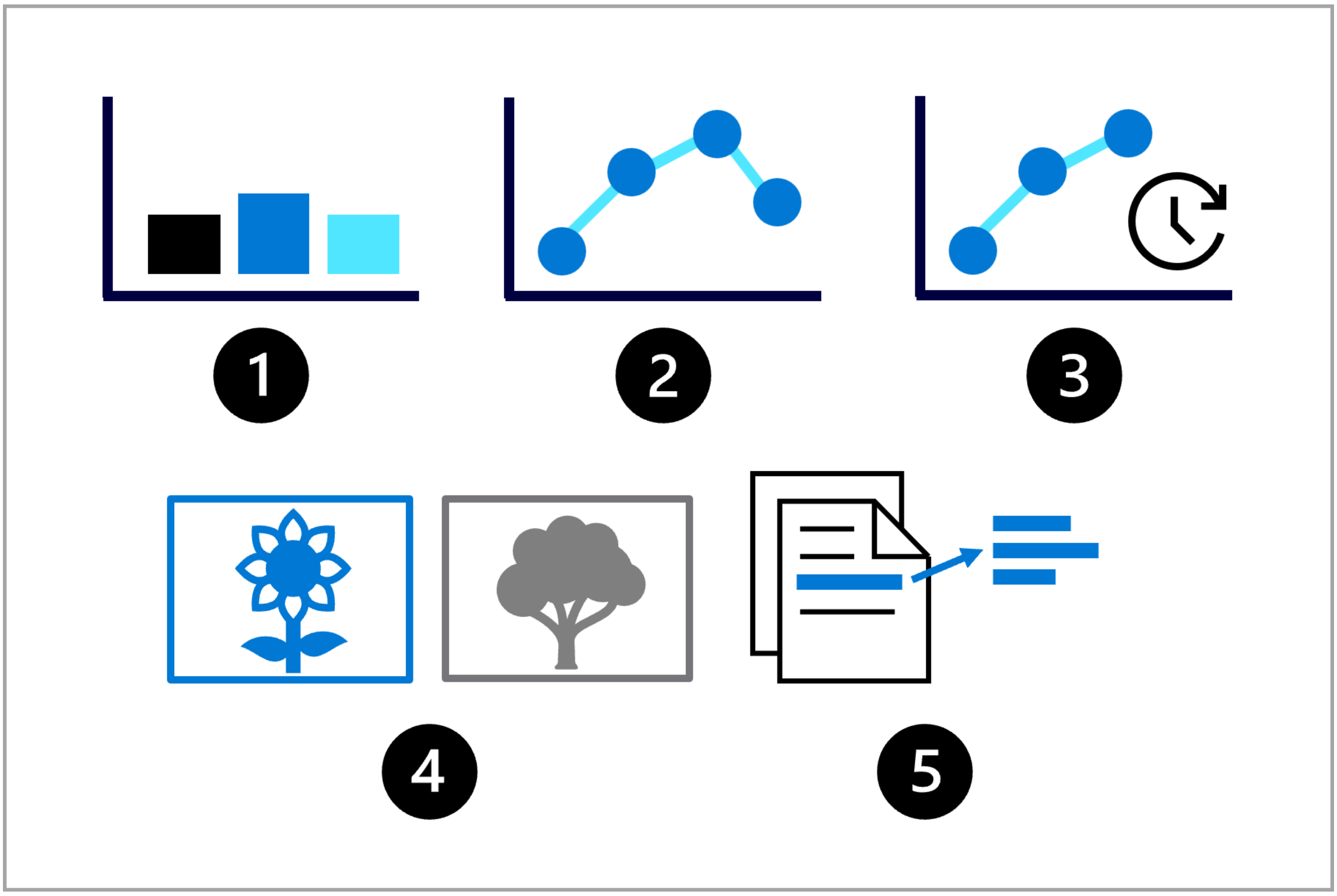
Common approach for a data ingestion solution:

- Extract raw data from its source (like a CRM system or IoT device).
- Copy and transform the data with Azure Synapse Analytics.
- Store the prepared data in an Azure Blob Storage.

- Train the model with Azure Machine Learning.



1.2 Design a machine learning model training solution



Some common machine learning tasks are:

- **Classification:** Predict a categorical value.
- **Regression:** Predict a numerical value.
- **Time-series forecasting:** Predict future numerical values based on time-series data.
- **Computer vision:** Classify images or detect objects in images.
- **Natural language processing (NLP):** Extract insights from text.

Multiple services would fit your scenario:

- Customizable prebuilt models suits your requirements - **Azure AI Services**

- Keep all data-related (data engineering and data science) projects within the same service - **Azure Synapse Analytics or Azure Databricks**
- Need distributed compute for working with large datasets (Large datasets & Work with PySpark) - **Azure Synapse Analytics or Azure Databricks**
- Full control over model training and management - **Azure Machine Learning or Azure Databricks**
- Python is your preferred programming language - **Azure Machine Learning**
- User interface to manage your machine learning lifecycle - **Azure Machine Learning**

> A Spark cluster consists of a driver node and worker nodes. **To make optimal use of a Spark cluster**, your code needs to be written in a **Spark-friendly language like Scala, SQL, RSpark, or PySpark** in order to distribute the workload. If you **write in Python**, **you'll only use the driver node** and leave the worker nodes unused.

1.3 Design a model deployment solution

When you deploy a model to an endpoint, you have two options:

- **real-time predictions** - Recommendations based on user search like tshirt recommend while browsing.
- **batch predictions** - Recommendations based on historal data like predict orange juice sales in future weeks.

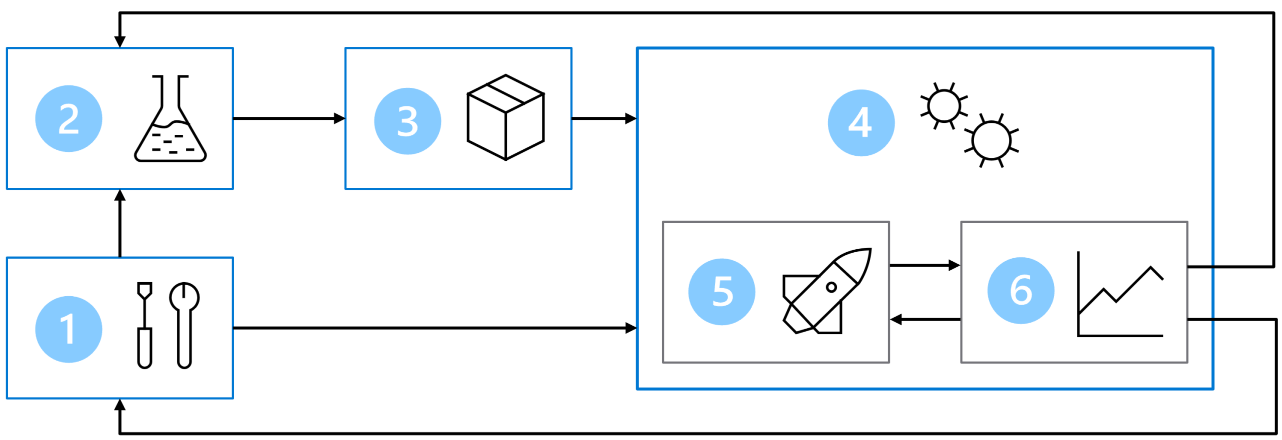
> ***Containers will be the more cost-effective solution as we want the model to be always available and respond immediately.***

1.4 Design a machine learning operations solution

To prepare the model and operationalize it, you want to:

- Convert the model training to a robust and reproducible pipeline.
- Test the code and the model in a development environment.
- Deploy the model in a production environment.
- Automate the end-to-end process.

MLOps Architecture:



Monitoring is beneficial in any MLOps environment.

> Model's predictions trained on older data less accurate.This change in data profiles between current and the training data is known as ***data drift***

> ***Important to be able to monitor data drift over time, and retrain models as required to maintain predictive accuracy.***

Two approaches to when you want to retrain a model:

- **Based on a schedule**
- **Based on metrics**

When the model's performance is below the benchmark, we should retrain the model.

> Two tools used in MLOps projects are **Azure DevOps** and **GitHub (Actions)**.

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2. Explore and configure the Azure Machine Learning workspace

2.1 Explore Azure Machine Learning workspace resources and assets

> - Azure administrators group to create compute targets and datastores
> - Data scientists group can create and run jobs to train models, and register models.

Resources and resource groups to assign permissions to other users:

- **Owner**
- **Contributor**
- **Reader**

Azure Machine Learning has specific built-in roles you can use:

- **AzureML Data Scientist:** Can perform all actions within the workspace, except for creating or deleting compute resources, or editing the workspace settings.
- **AzureML Compute Operator:** Is allowed to create, change, and manage access the compute resources within a workspace.

Five types of compute in the Azure Machine Learning workspace:

- Compute instances
- Compute clusters
- Kubernetes clusters
- Attached computes
- Serverless compute

Four datastores already added to your workspace:

- workspaceartifactstore
- workspaceworkingdirectory
- workspaceblobstore

- workspacefilestore

To train models with the Azure Machine Learning workspace, you have several options:

- Use Automated Machine Learning.
- Run a Jupyter notebook.
- Run a script as a job.

There are different types of jobs depending on how you want to execute a workload:

- **Command:** Execute a single script.
- **Sweep:** Perform hyperparameter tuning when executing a single script.
- **Pipeline:** Run a pipeline consisting of multiple scripts or components.

2.2 Explore developer tools for workspace interaction

Azure Machine Learning studio access:

- **Author:** Create new jobs to train and track a machine learning model.
- **Assets:** Create and review assets you use when training models.
- **Manage:** Create and manage resources you need to train models.

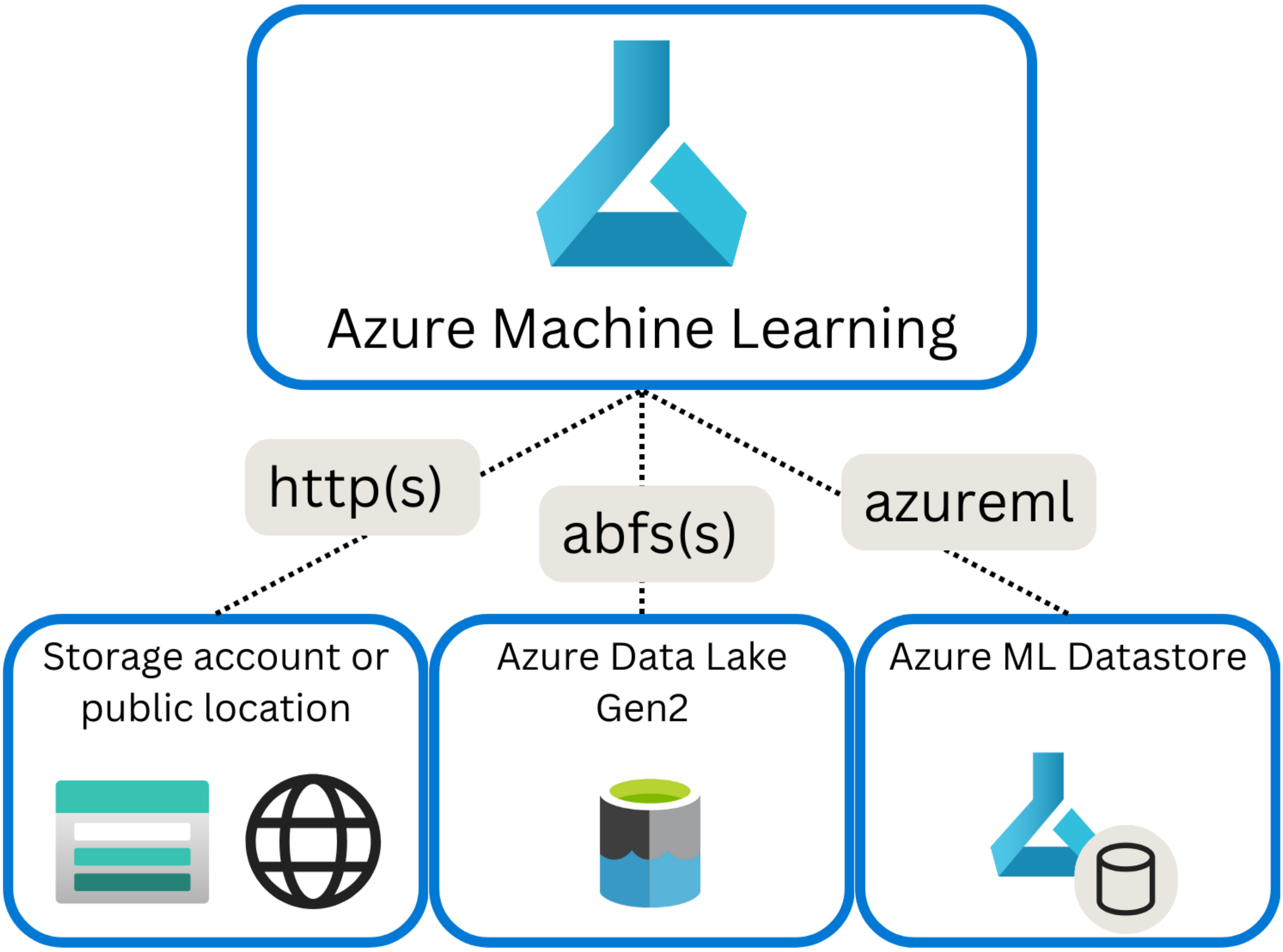
Create a new job to train a model:

```
from azure.ai.ml import command
# configure job
job = command(
    code="./src",
    command="python train.py",
    environment="AzureML-sklearn-0.24-ubuntu18.04-py37-cpu@latest",
    compute="aml-cluster",
    experiment_name="train-model"
)
# connect to workspace and submit job
returned_job = ml_client.create_or_update(job)
```

Azure CLI allows you to:

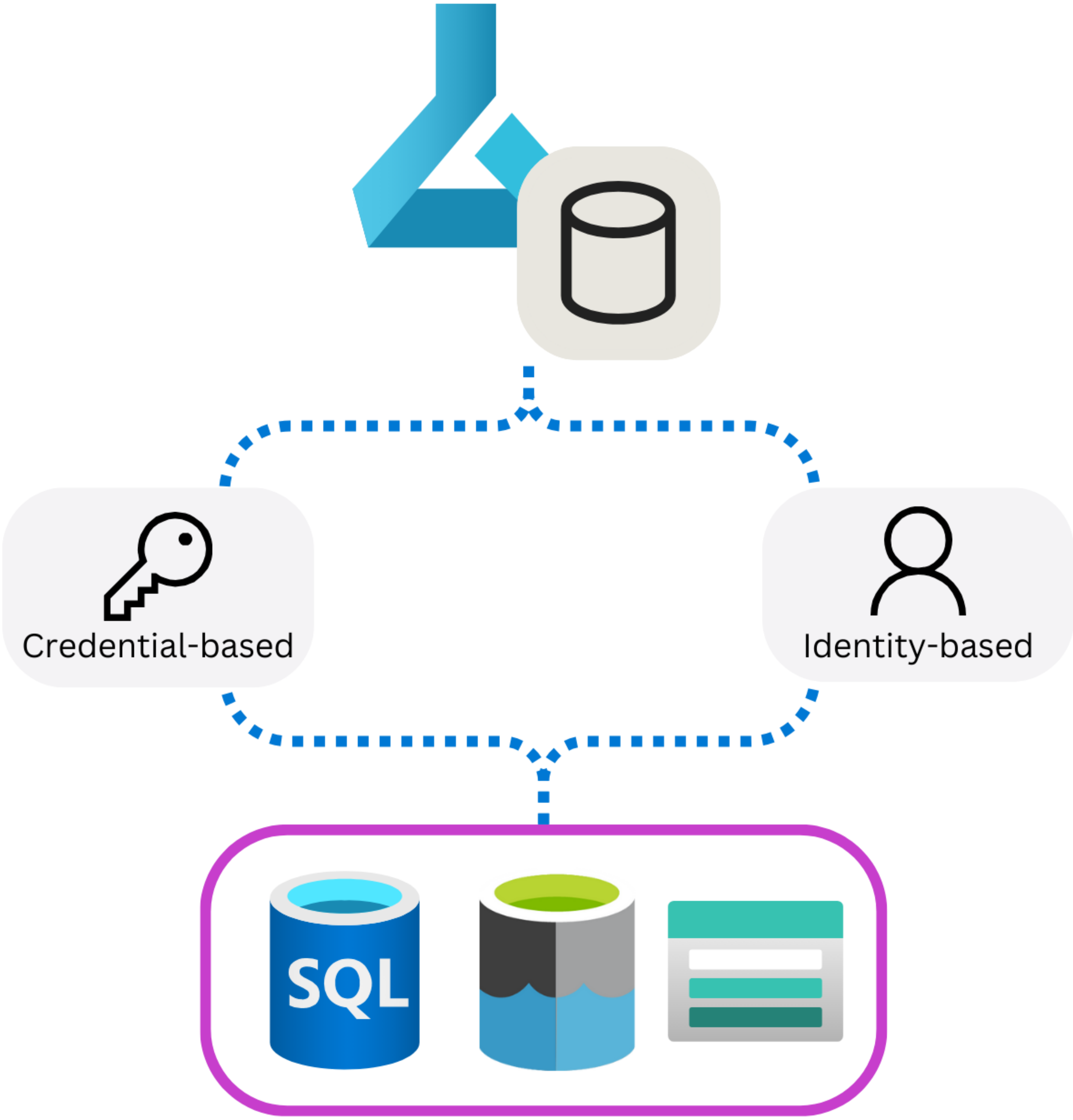
- Automate the creation and configuration of assets and resources to make it repeatable.
- Ensure consistency for assets and resources that must be replicated in multiple environments (for example, development, test, and production).
- Incorporate machine learning asset configuration into developer operations (DevOps) workflows, such as continuous integration and continuous deployment (CI/CD) pipelines.

2.3 Make data available in Azure Machine Learning



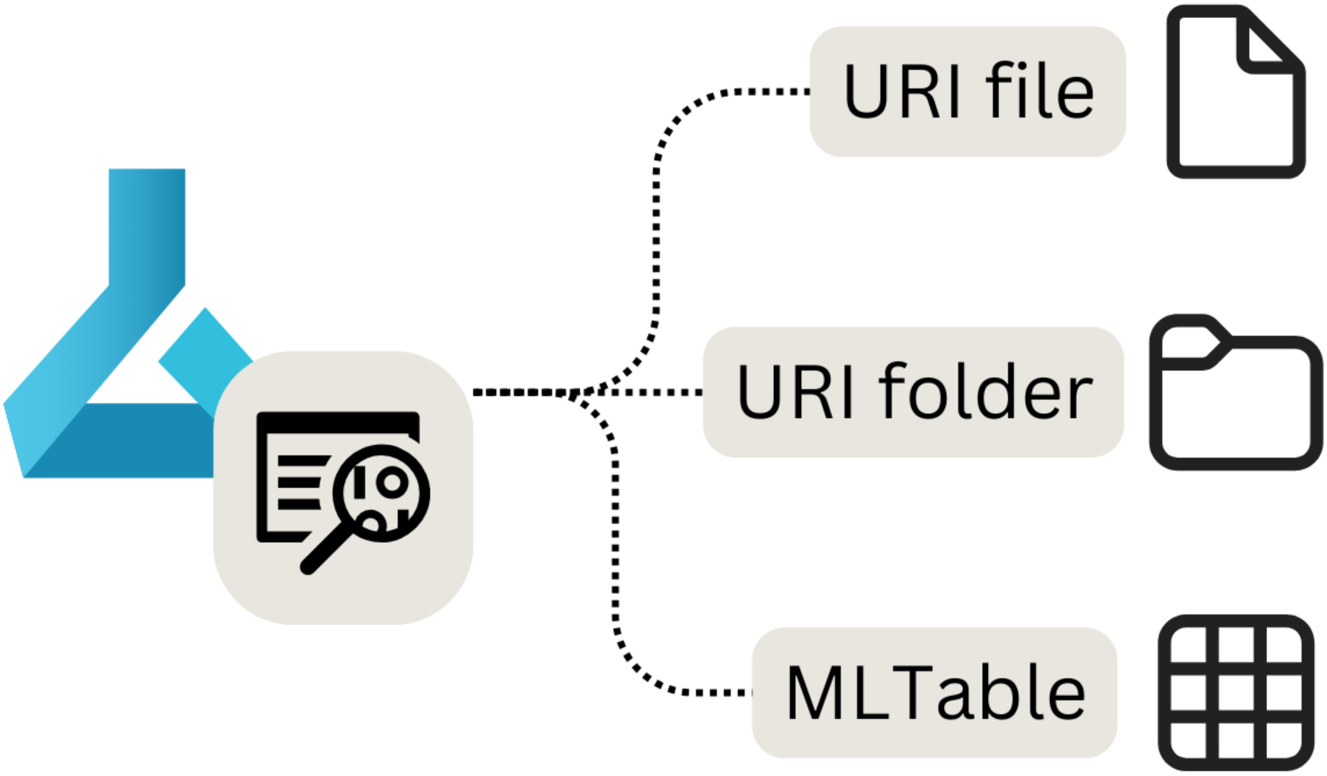
Data Store location:

- **http(s):** Use for data stores publicly or privately in an Azure Blob Storage or publicly available http(s) location.
- **abfs(s):** Use for data stores in an Azure Data Lake Storage Gen 2.
- **azureml:** Use for data stored in a datastore.



Access granted permission:

- **Credential-based:** Use a service principal, shared access signature (SAS) token or account key to authenticate access to your storage account.
- **Identity-based:** Use your Microsoft Entra identity or managed identity.



Access file/data from location:

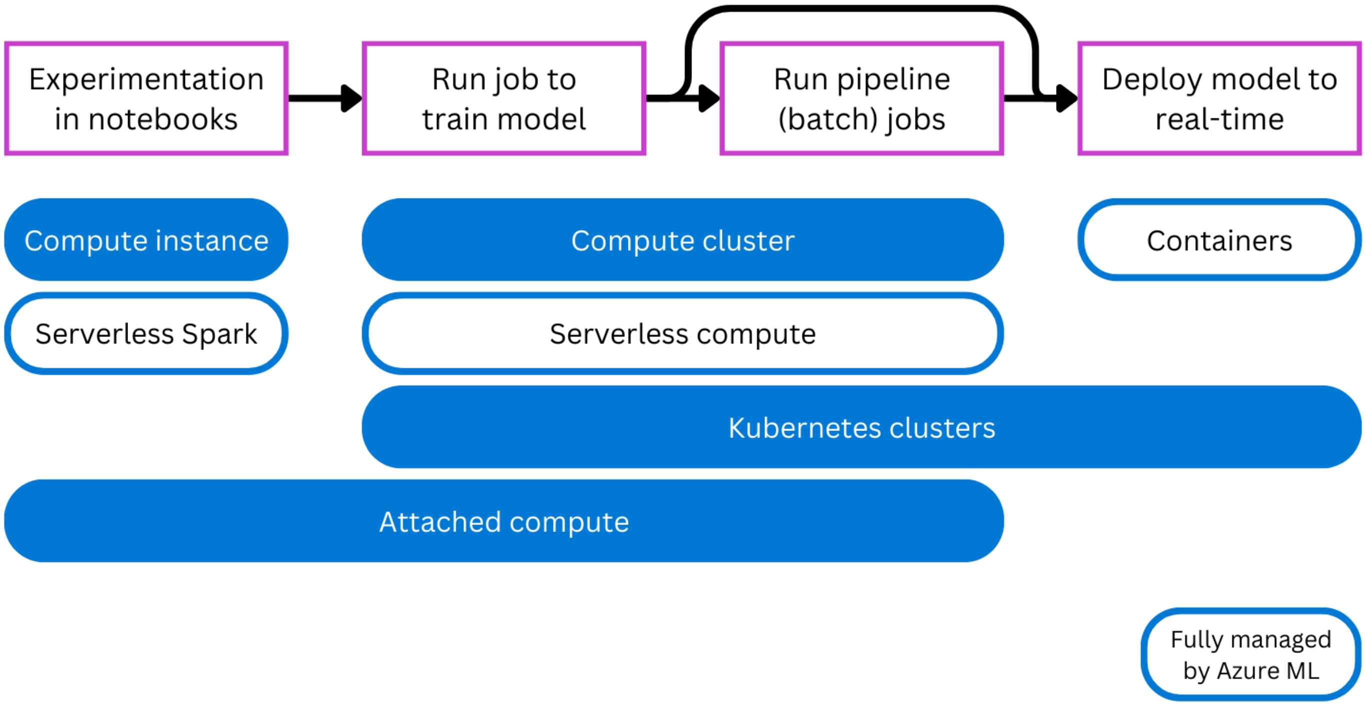
- **URI file:** Points to a specific file.
- **URI folder:** Points to a folder.
- **MLTable:** Points to a folder or file, and includes a schema to read as tabular data.

> ***MLTable*** *is ideal when the schema changes frequently. Then, you only need to make changes in one location instead of multiple.*

To create a URI file data asset:

```
from azure.ai.ml.entities import Data
from azure.ai.ml.constants import AssetTypes
my_path = '<supported-path>'
my_data = Data(
    path=my_path,
    type=AssetTypes.URI_FILE,
    description="<description>",
    name="<name>",
    version="<version>"
)
ml_client.data.create_or_update(my_data)
```

2.4 Work with compute targets in Azure Machine Learning



To create a compute cluster with the Python SDK:

```
from azure.ai.ml.entities import AmlCompute
cluster_basic = AmlCompute(
    name="cpu-cluster",
    type="amlcompute",
    size="STANDARD_DS3_v2",
    location="westus",
    min_instances=0,
    max_instances=2,
    idle_time_before_scale_down=120,
    tier="low_priority",
)
ml_client.begin_create_or_update(cluster_basic).result()
```

When you create a compute cluster, there are three main parameters:

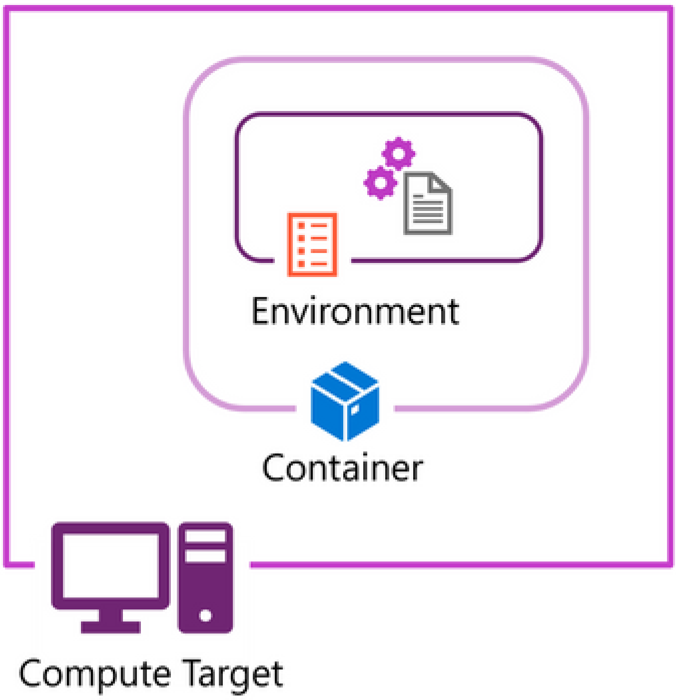
- **size** - Specifies the virtual machine type of each node within the compute cluster
- **max_instances** - Specifies the maximum number of nodes your compute cluster can scale out to.
- **tier** - Specifies whether your virtual machines are low priority or dedicated

Three main scenarios in which you can use a compute cluster:

- Running a pipeline job you built in the Designer.
- Running an Automated Machine Learning job.
- Running a script as a job.

> *By increasing the idle time before scale down, you can run multiple pipelines consecutively without the compute cluster resizing to zero nodes in between jobs.*

2.5 Work with environments in Azure Machine Learning



Retrieve an environment by its registered name:

```
env = ml_client.environments.get(name="my-environment", version="1")
print(env)
```

> **Curated environments are ideal to use for faster development time.**

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3. Experiment with Azure Machine Learning

3.1 Find the best classification model with Automated Machine Learning

AutoML applies scaling and normalization to numeric data automatically, helping prevent any large-scale features from dominating training.

- By default, AutoML will perform featurization on your data.

***AutoML** needs a MLTable data asset as input. In the example, my_training_data_input refers to a MLTable data asset created in the Azure Machine Learning workspace.*

3.2 Track model training in Jupyter notebooks with MLflow

MLflow is an open-source library for tracking and managing your machine learning experiments.

- The *mlflow* package is the open-source library. The *azureml-mlflow* package contains the integration code of Azure Machine Learning with MLflow.

- MLflow supports automatic logging for popular machine learning libraries

- You can use **autologging with scikit-learn**. Enabling autologging will minimize the effort needed to log the model's results.
- Jobs will show the **MLflow experiment runs** including all metadata and logged parameters, metrics, and artifacts.

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4. Optimize model training with Azure Machine Learning

4.1 Run a training script as a command job in Azure Machine Learning

***Scripts are ideal for testing and automation in your production environment.* To create a production-ready script:**

- Remove nonessential code.
- Refactor your code into functions.
- Test your script in the terminal.

You can configure a command job to run a file named *train.py*, on the compute cluster named *aml-cluster* with the following code:

```
from azure.ai.ml import command
# configure job
job = command(
    code="./src",
    command="python train.py",
    environment="AzureML-sklearn-0.24-ubuntu18.04-py37-cpu@latest",
    compute="aml-cluster",
    display_name="train-model",
    experiment_name="train-classification-model"
    )
```

> - `command` - To configure a command job
> - `argparse` - To use parameters in a script,

> - To use different values each time, define arguments in the script and pass them using the arguments parameter of the command job.

4.2 Track model training with MLflow in jobs

MLflow is an open-source platform, designed to manage the complete machine learning lifecycle.

Two options to track machine learning jobs with MLflow:

- Enable autologging using `mlflow.autolog()`
- Use logging functions to track custom metrics using `mlflow.log_*`

Use the MLflow command to store the metric with the experiment run:

- `mlflow.log_param()`: Log single key-value parameter. Use this function for an input parameter you want to log.
- `mlflow.log_metric()`: Log single key-value metric. Value must be a number. Use this function for any output you want to store with the run.
- `mlflow.log_artifact()`: Log a file. Use this function for any plot you want to log, save as image file first.

> **Use mlflow.log_metric() to log a metric like the RMSE. Model assets like the model pickle file will be stored in the model folder under Outputs + logs.**

```
import mlflow
reg_rate = 0.1
mlflow.log_param("Regularization rate", reg_rate)
```

> MLflow allows you to search for runs inside of any experiment. You need either the experiment ID or the experiment name.

if you want to sort by start time and only show the last two results:

```
mlflow.search_runs(exp.experiment_id, order_by=["start_time DESC"], max_results=2)
```

4.3 Perform hyperparameter tuning with Azure Machine Learning

> The set of hyperparameter values tried during hyperparameter tuning is known as the `search space`

Some **hyperparameters require discrete values**. You can also select discrete values from any of the following discrete distributions:

- `QUniform(min_value, max_value, q)`: Returns a value like round(Uniform(min_value, max_value) / q) * q
- `QLogUniform(min_value, max_value, q)`: Returns a value like round(exp(Uniform(min_value, max_value)) / q) * q
- `QNormal(mu, sigma, q)`: Returns a value like round(Normal(mu, sigma) / q) * q
- `QLogNormal(mu, sigma, q)`: Returns a value like round(exp(Normal(mu, sigma)) / q) * q

To define a search space for these kinds of value, you can use any of the following distribution types:

- `Uniform(min_value, max_value)`: Returns a value uniformly distributed between min_value and max_value
- `LogUniform(min_value, max_value)`: Returns a value drawn according to exp(Uniform(min_value, max_value)) so that the logarithm of the return value is uniformly distributed
- `Normal(mu, sigma)`: Returns a real value that's normally distributed with mean mu and standard deviation sigma
- `LogNormal(mu, sigma)`: Returns a value drawn according to exp(Normal(mu, sigma)) so that the logarithm of the return value is normally distributed

To define a search space for hyperparameter tuning, create a dictionary with the appropriate parameter expression for each named hyperparameter.

```
from azure.ai.ml.sweep import Choice, Normal
command_job_for_sweep = job(
    batch_size=Choice(values=[16, 32, 64]),
    learning_rate=Normal(mu=10, sigma=3),
)
```

Three main sampling methods available in Azure Machine Learning:

- **Grid sampling**: Tries every possible combination.
- **Random sampling**: Randomly chooses values from the search space.
  - **Sobol**: Adds a seed to random sampling to make the results reproducible.
- **Bayesian sampling**: Chooses new values based on previous results.

Two main parameters when you choose to use an early termination policy:

- **evaluation_interval**: Specifies at which interval you want the policy to be evaluated. Every time the primary metric is logged for a trial counts as an interval.
- **delay_evaluation**: Specifies when to start evaluating the policy. This parameter allows for at least a minimum of trials to complete without an early termination policy affecting them.

To determine the extent to which a model should perform better than previous trials, there are three options for early termination:

- **Bandit policy**: Uses a slack_factor (relative) or slack_amount(absolute). Any new model must perform within the slack range of the best performing model.
- **Median stopping policy**: Uses the median of the averages of the primary metric. Any new model must perform better than the median.
- **Truncation selection policy**: Uses a truncation_percentage, which is the percentage of lowest performing trials. Any new model must perform better than the lowest performing trials.

4.4 Run pipelines in Azure Machine Learning

Two main reasons why you'd use components:

- To build a pipeline.
- To share ready-to-go code.

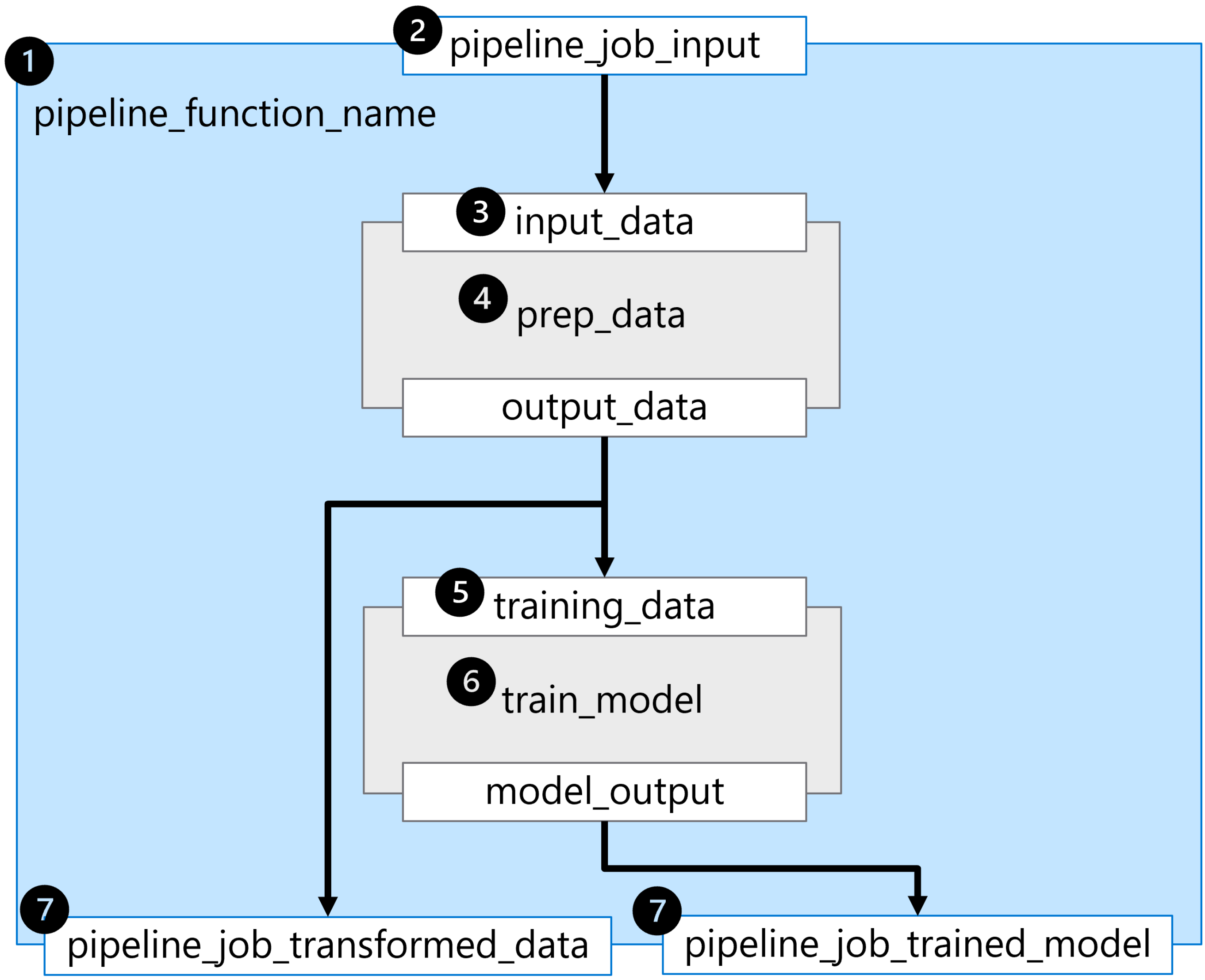
A component consists of three parts:

- `Metadata`: Includes the component's name, version, etc.
- `Interface`: Includes the expected input parameters (like a dataset or hyperparameter) and expected output (like metrics and artifacts).
- `Command, code and environment`: Specifies how to run the code.

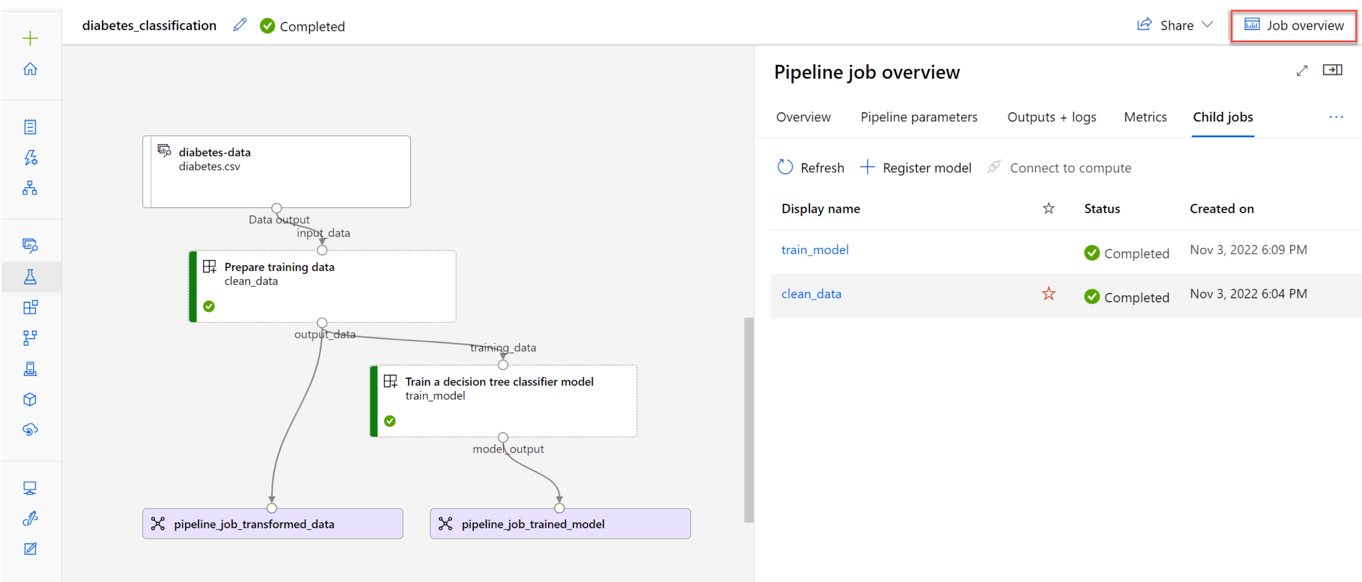
To create a component, you need two files:

- A script that contains the workflow you want to execute.

- A YAML file to define the metadata, interface, and command, code, and environment of the component.



A pipeline is defined in a YAML file, which you can also create using the `@pipeline()` function.



Various ways to create a schedule:

- **frequency**

- **interval**

> RecurrenceTrigger class to create a schedule that runs at a regular interval.

To create a schedule that fires every minute, run the following code:

```
from azure.ai.ml.entities import RecurrenceTrigger
schedule_name = "run_every_minute"
recurrence_trigger = RecurrenceTrigger(
    frequency="minute",
    interval=1,
)
```

5. Manage and review models in Azure Machine Learning

5.1 Register an MLflow model in Azure Machine Learning

When you train and log a model, you store all relevant artifacts in a directory. When you register the model, an `MLmodel` file is created in that directory. The `MLmodel` file contains the model's metadata, which allows for model traceability.

> You want your model to be identified as by using `mlflow.<flavor>.autolog()`

The MLmodel file may include:

- `artifact_path`: During the training job, the model is logged to this path.
- `flavor`: The machine learning library with which the model was created.
- `model_uuid`: The unique identifier of the registered model.
- `run_id`: The unique identifier of job run during which the model was created.
- `signature`: Specifies the schema of the model's inputs and outputs:
  - `inputs`: Valid input to the model. For example, a subset of the training dataset.
  - `outputs`: Valid model output. For example, model predictions for the input dataset.

Two types of signatures:

- `Column-based`: used for tabular data with a pandas.Dataframe as inputs.
- `Tensor-based`: used for n-dimensional arrays or tensors (often used for unstructured data like text or images), with numpy.ndarray as inputs.

Three types of models you can register:

- `MLflow`: Model trained and tracked with MLflow. Recommended for standard use cases.
- `Custom`: Model type with a custom standard not currently supported by Azure Machine Learning.
- `Triton`: Model type for deep learning workloads. Commonly used for TensorFlow and PyTorch model deployments.

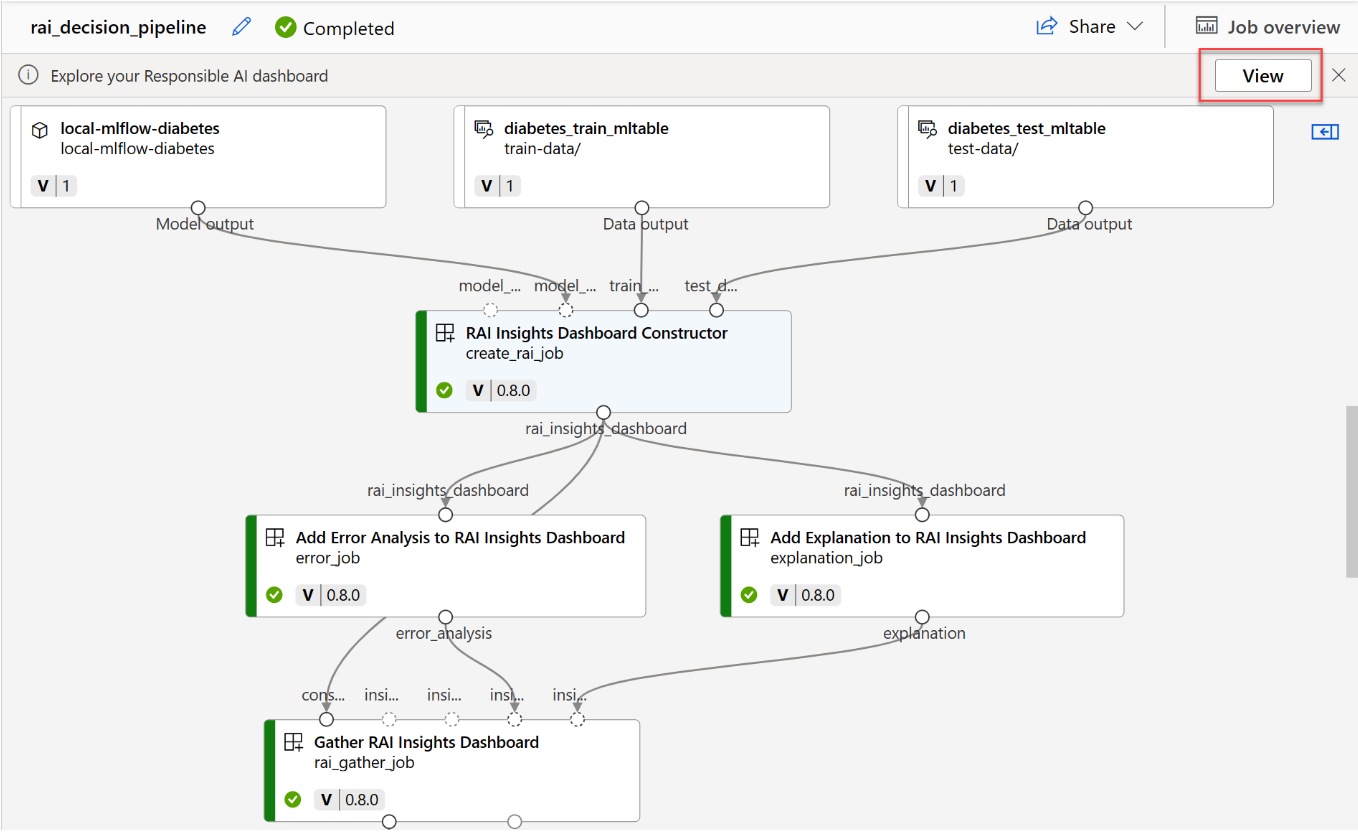
5.2 Create and explore the Responsible AI dashboard for a model in Azure Machine Learning

Microsoft has listed five Responsible AI principles:

- Fairness and inclusiveness
- Reliability and safety
- Privacy and security
- Transparency
- Accountability

To create a Responsible AI (RAI) dashboard, you need to create a pipeline by using the built-in components. The pipeline should:

1. Start with the `RAI Insights dashboard constructor`.
2. Include one of the RAI tool components.
3. End with `Gather RAI Insights dashboard` to collect all insights into one dashboard.
4. Optionally you can also add the `Gather RAI Insights score card` at the end of your pipeline.



You can create the Responsible AI dashboard in three ways:

- Using the Command Line Interface (CLI) extension for Azure Machine Learning.
- Using the Python Software Development Kit (SDK).
- Using the Azure Machine Learning studio for a no-code experience.

Insights in your Responsible AI dashboard:

1. Error analysis
2. Explanations

3. Counterfactuals
4. Causal analysis

Explore error analysis -

- `Error tree map`: Allows you to explore which combination of subgroups results in the model making more false predictions.
- `Error heat map`: Presents a grid overview of a model's errors over the scale of one or two features.

Explore explanations -

- `Aggregate feature importance`: Shows how each feature in the test data influences the model's predictions overall.
- `Individual feature importance`: Shows how each feature impacts an individual prediction.

**Causal analysis - **

- `Aggregate causal effects`: Shows the average causal effects for predefined treatment features (the features you want to change to optimize the model's predictions).
- `Individual causal effects`: Shows individual data points and allows you to change the treatment features to explore their influence on the prediction.
- `Treatment policy`: Shows which parts of your data points benefit most from a treatment.

6. Deploy and consume models with Azure Machine Learning

6.1 Deploy a model to a managed online endpoint

To get real-time predictions, you can deploy a model to an endpoint. An endpoint is an HTTPS endpoint to which you can send data, and which will return a response (almost) immediately.

Within Azure Machine Learning, there are two types of online endpoints:

- **Managed online endpoints**: Azure Machine Learning manages all the underlying infrastructure.
- **Kubernetes online endpoints**: Users manage the Kubernetes cluster which provides the necessary infrastructure.

To deploy your model to a managed online endpoint, you need to specify four things:

- **Model assets** like the model pickle file, or a registered model in the Azure Machine Learning workspace.
- **Scoring script** that loads the model.
- **Environment** which lists all necessary packages that need to be installed on the compute of the endpoint.
- **Compute configuration** including the needed compute size and scale settings to ensure you can handle the amount of requests the endpoint will receive.

> - One endpoint can have multiple deployments. *One approach is the blue/green deployment.*
> - **Blue/green deployment **allows for multiple models to be deployed to an endpoint.

To create an endpoint, use the following command:

```
from azure.ai.ml.entities import ManagedOnlineEndpoint
# create an online endpoint
endpoint = ManagedOnlineEndpoint(
    name="endpoint-example",
    description="Online endpoint",
    auth_mode="key",
)
ml_client.begin_create_or_update(endpoint).result()
```

Need to specify the compute configuration for the deployment:

- **instance_type**: Virtual machine (VM) size to use. Review the list of supported sizes.
- **instance_count**: Number of instances to use.

To deploy a model, you must have:

- Model files stored on local path or registered model.
- A scoring script.
- An execution environment.

6.2 Deploy a model to a batch endpoint

> To get batch predictions, you can deploy a model to an endpoint.

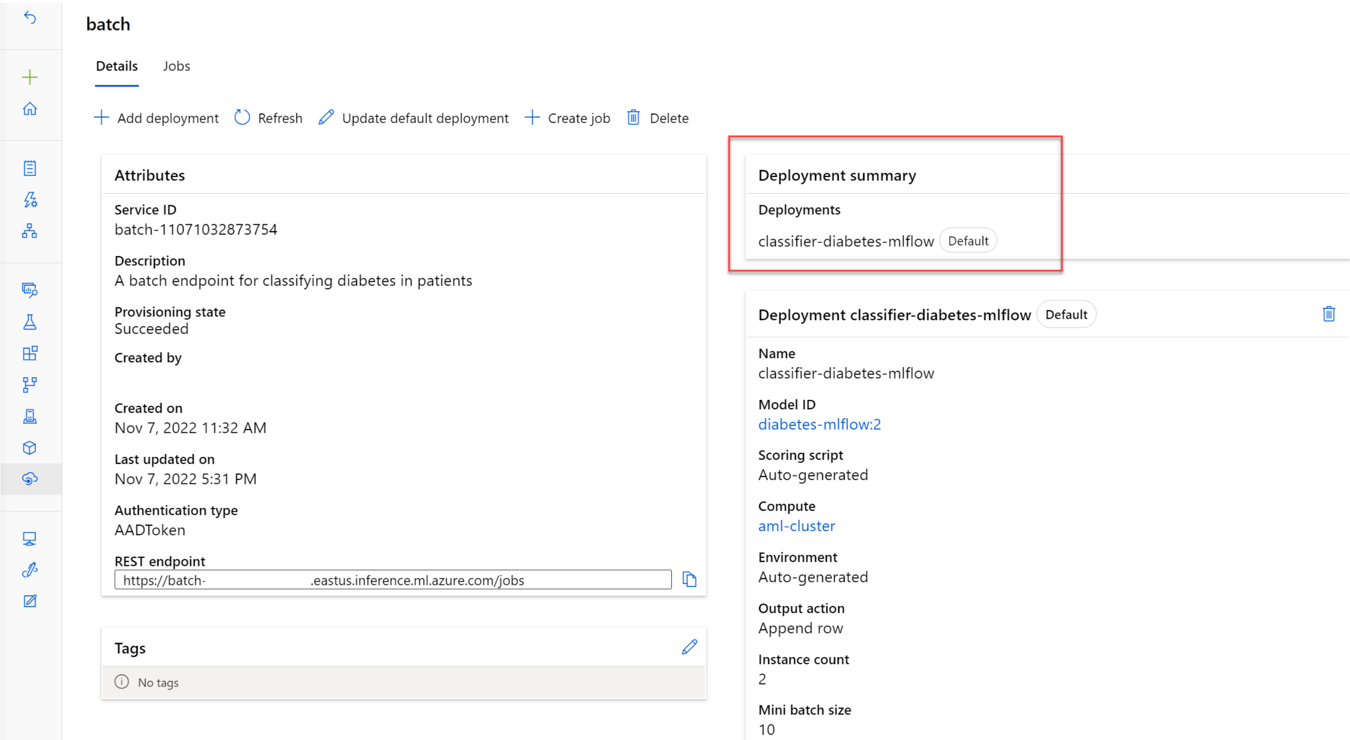
To create an endpoint, use the following command:

```
# create a batch endpoint
endpoint = BatchEndpoint(
    name="endpoint-example",
    description="A batch endpoint",
)
ml_client.batch_endpoints.begin_create_or_update(endpoint)
```

> *To avoid needed a scoring script and environment, an MLflow model needs to be registered in the Azure Machine Learning workspace before you can deploy it to a batch endpoint.*

When you configure the model deployment, you can specify:

- **instance_count**: Count of compute nodes to use for generating predictions.
- **max_concurrency_per_instance**: Maximum number of parallel scoring script runs per compute node.
- **mini_batch_size**: Number of files passed per scoring script run.
- **output_action**: What to do with the predictions: summary_only or append_row.
- **output_file_name**: File to which predictions will be appended, if you choose append_row for output_action.

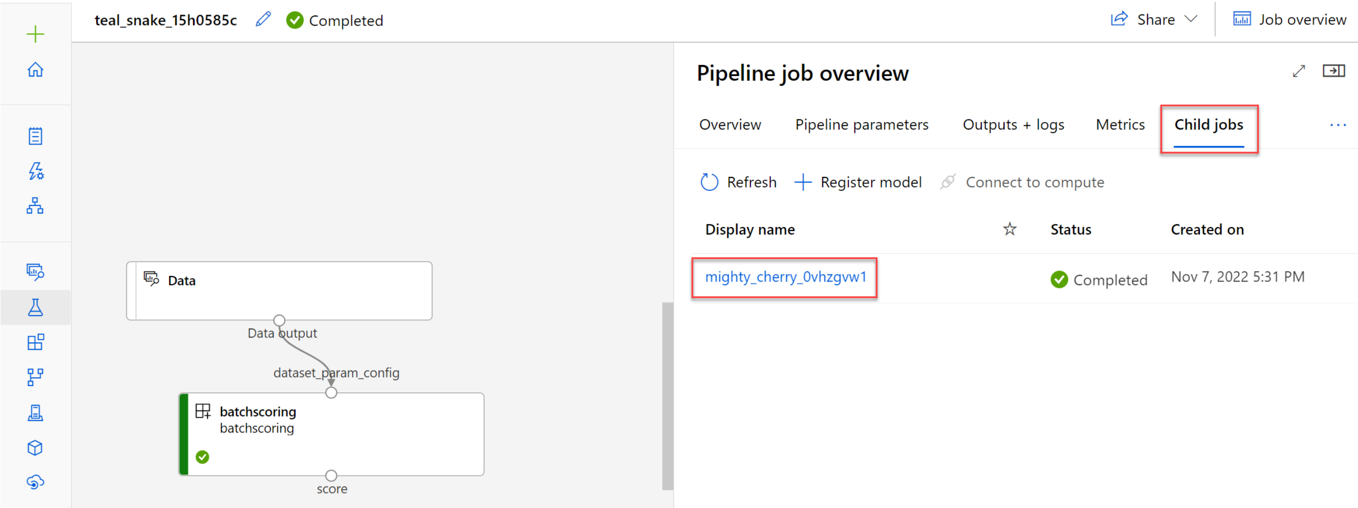


To deploy an MLflow model to a batch endpoint, you can use the following code:

```
from azure.ai.ml.entities import BatchDeployment, BatchRetrySettings
from azure.ai.ml.constants import BatchDeploymentOutputAction
deployment = BatchDeployment(
    name="forecast-mlflow",
    description="A sales forecaster",
    endpoint_name=endpoint.name,
    model=model,
    compute="aml-cluster",
    instance_count=2,
    max_concurrency_per_instance=2,
    mini_batch_size=2,
    output_action=BatchDeploymentOutputAction.APPEND_ROW,
    output_file_name="predictions.csv",
    retry_settings=BatchRetrySettings(max_retries=3, timeout=300),
    logging_level="info",
)
ml_client.batch_deployments.begin_create_or_update(deployment)
```

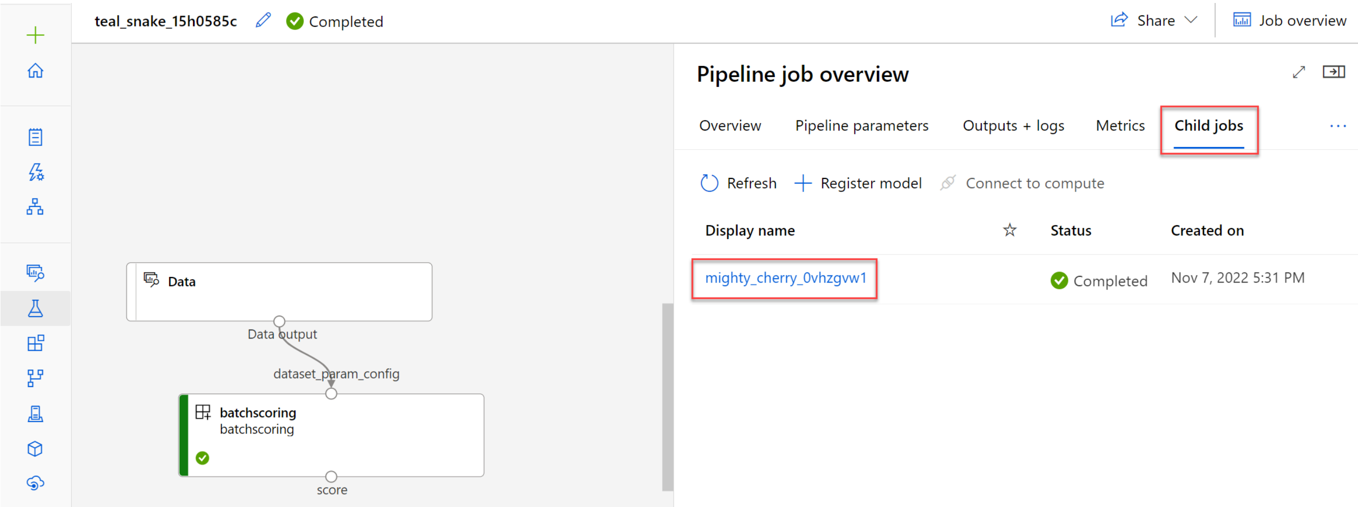
The scoring script must include two functions:

- **init()**: Called once at the beginning of the process, so use for any costly or common preparation like loading the model.
- **run()**: Called for each mini batch to perform the scoring.



The logs/user/ folder contains three files that will help you troubleshoot:

- **job_error.txt**: Summarize the errors in your script.
- **job_progress_overview.txt**: Provides high-level information about the number of mini-batches processed so far.
- **job_result.txt**: Shows errors in calling the init() and run() function in the scoring script.



> *The default deployment will be used to do the actual batch scoring when the endpoint is invoked.*