Advanced Machine Learning on Azure

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Agenda

2 components of model operationalization

Model deployment workflow

Automated machine learning

Model deployment workflow

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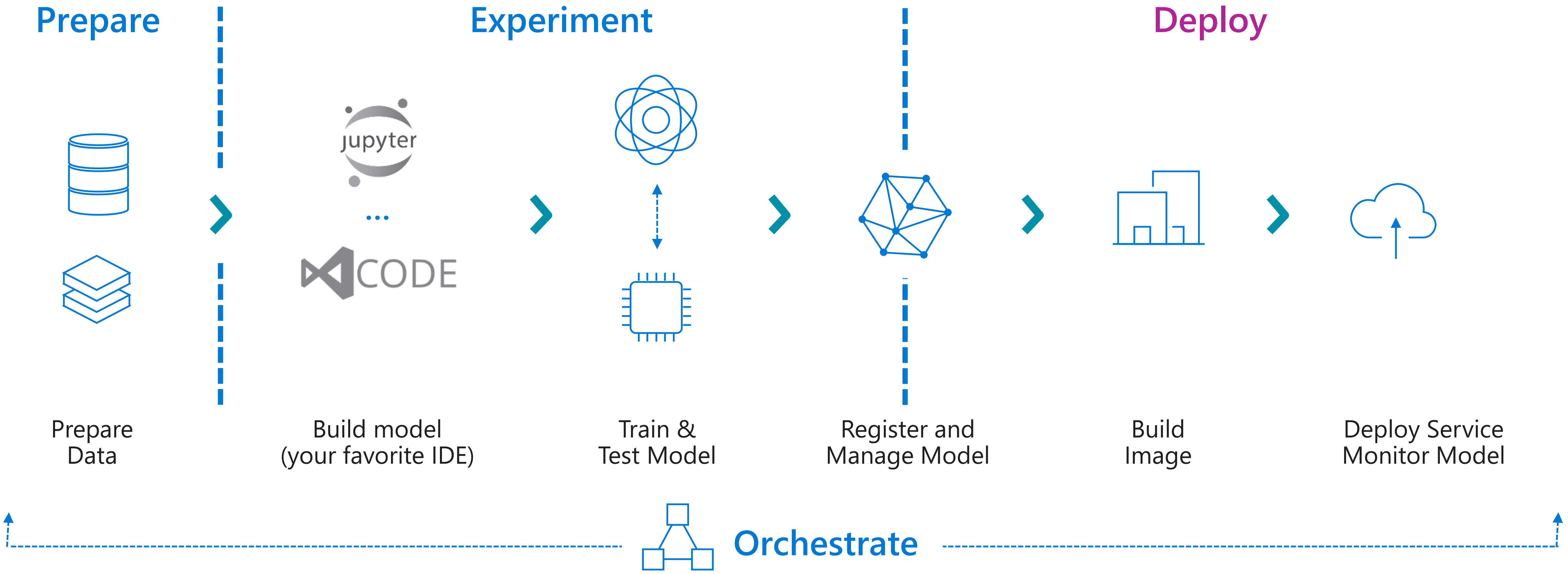
Machine Learning

Typical End To End Process



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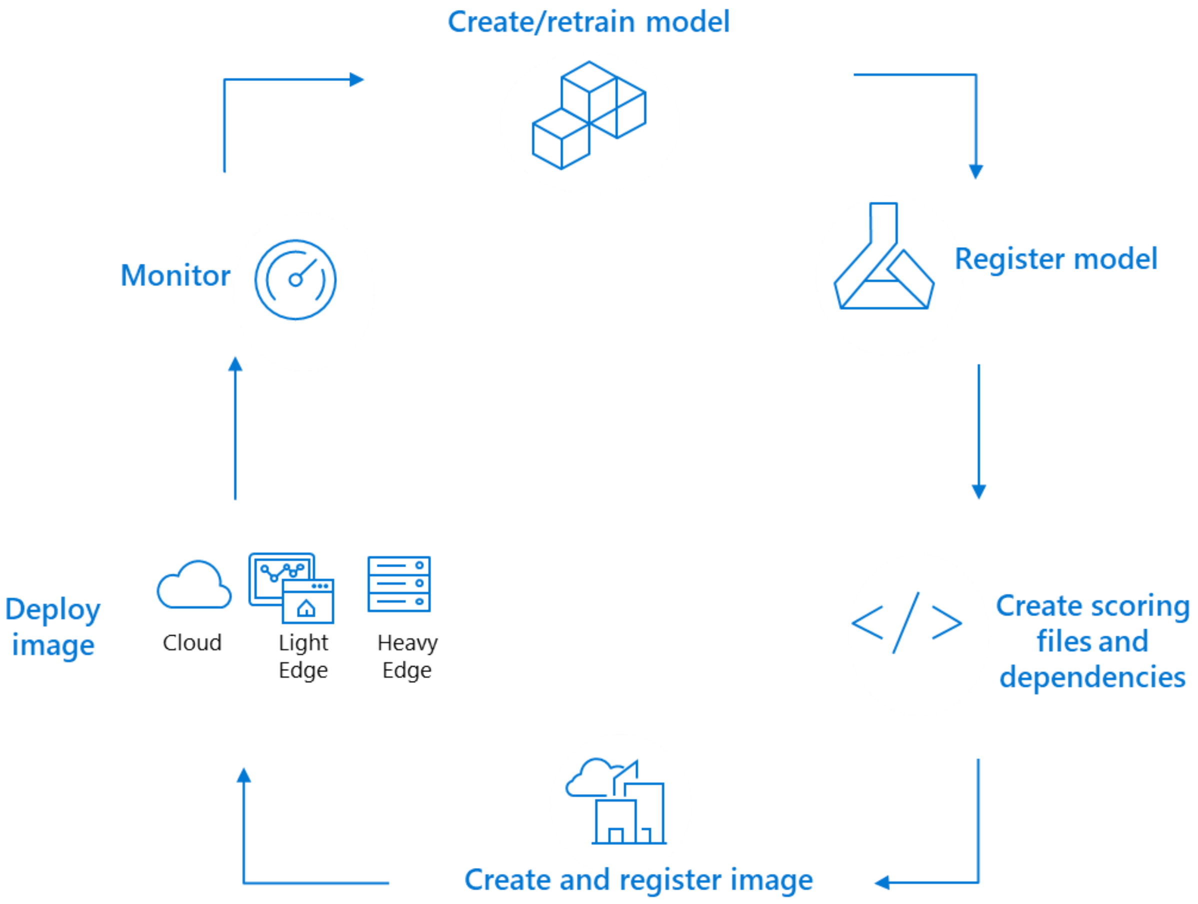
Manage model lifecycle

- **Track model versions and metadata** with a centralized model registry
- **Leverage containers** to capture runtime dependencies for inference
- Leverage an **orchestrator** like Kubernetes to provide scalable inference
- Capture **model telemetry** – health, performance, inputs/outputs
- Encapsulate each step in the lifecycle to enable **CI/CD and DevOps**
- Automatically **optimize models** to take advantage of hardware acceleration



Model deployment workflow

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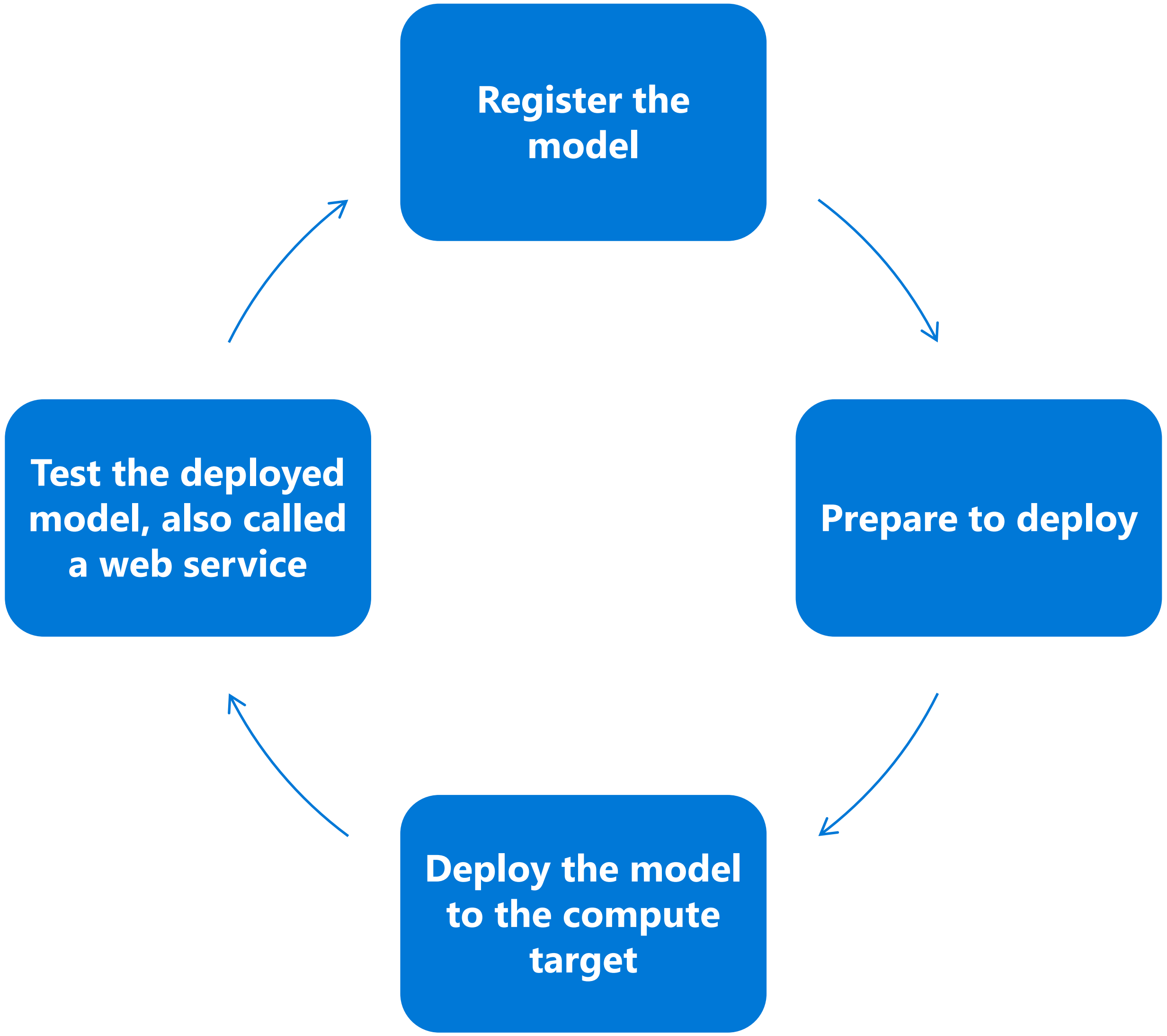
The workflow is similar no matter where you deploy your model:



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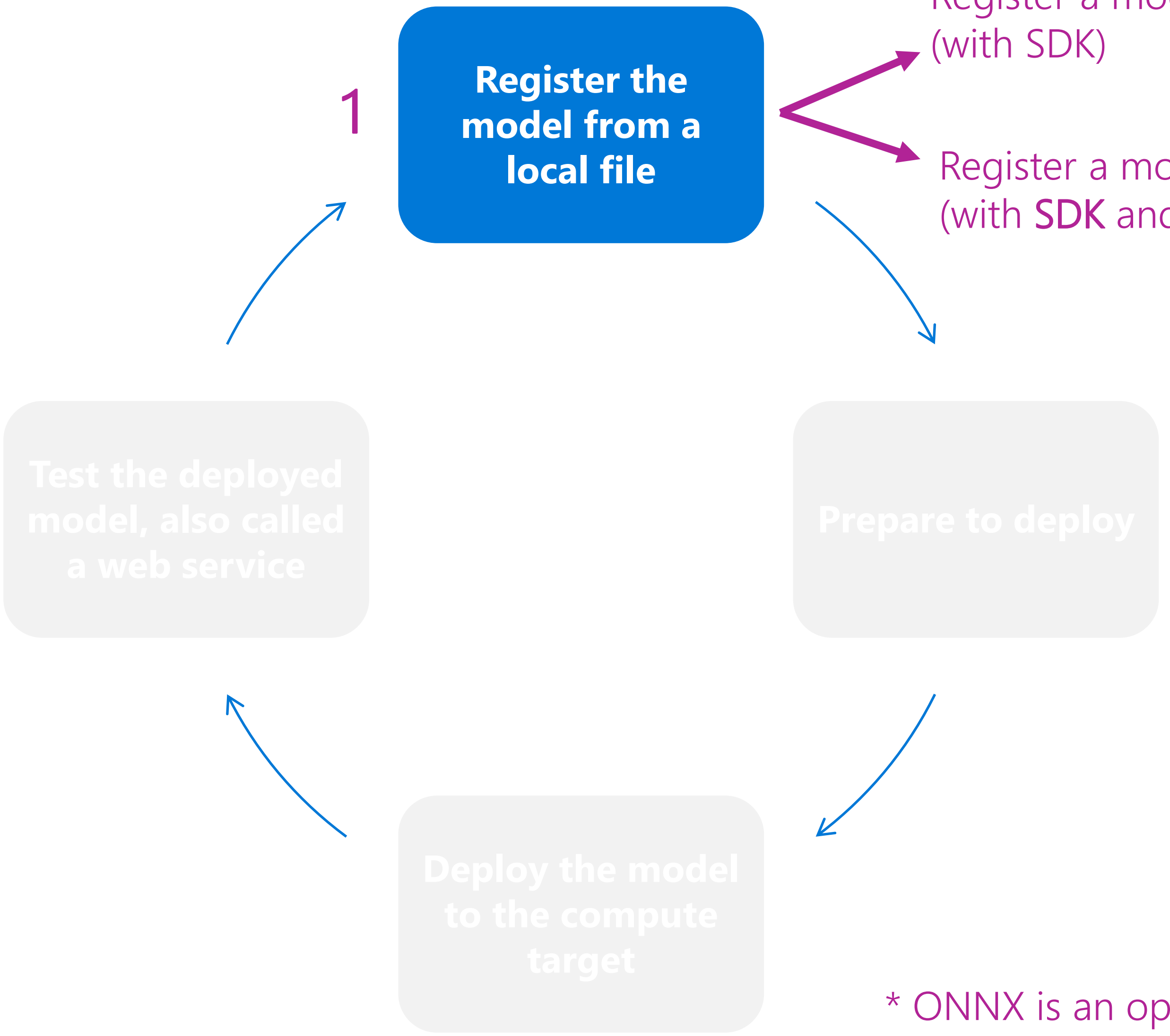

Register a model from an experiment run (with SDK)

Register a model from a local file (with SDK and ONNX*)

* ONNX is an open format built to represent machine learning models - https://onnx.ai/

Step 1 – Register the model (Run Object)

```
model = run.register_model(model_name='sklearn_mnist',
                           tags={'area': 'mnist'},
                           model_path='outputs/sklearn_mnist_model.pkl’)

print(model.name, model.id, model.version, sep='\t')
```

OR…

Step 1 – Register the model (AutoMLRun Object)

```
description = 'My AutoML Model'
    model = run.register_model(description = description,
                               tags={'area': 'mnist'})

    print(run.model_id)
```

Step 1 – Register a model from a local file

```
import os
import urllib.request
from azureml.core.model import Model

# Download model
onnx_model_url = "https://www.cntk.ai/OnnxModels/mnist/opset_7/mnist.tar.gz"
urllib.request.urlretrieve(onnx_model_url, filename="mnist.tar.gz")
os.system('tar xvzf mnist.tar.gz')

# Register model
model = Model.register(workspace = ws,
                        model_path ="mnist/model.onnx",
                        model_name = "onnx_mnist",
                        tags = {"onnx": "demo"},
                        description = "MNIST image classification CNN from ONNX Model Zoo",)
```

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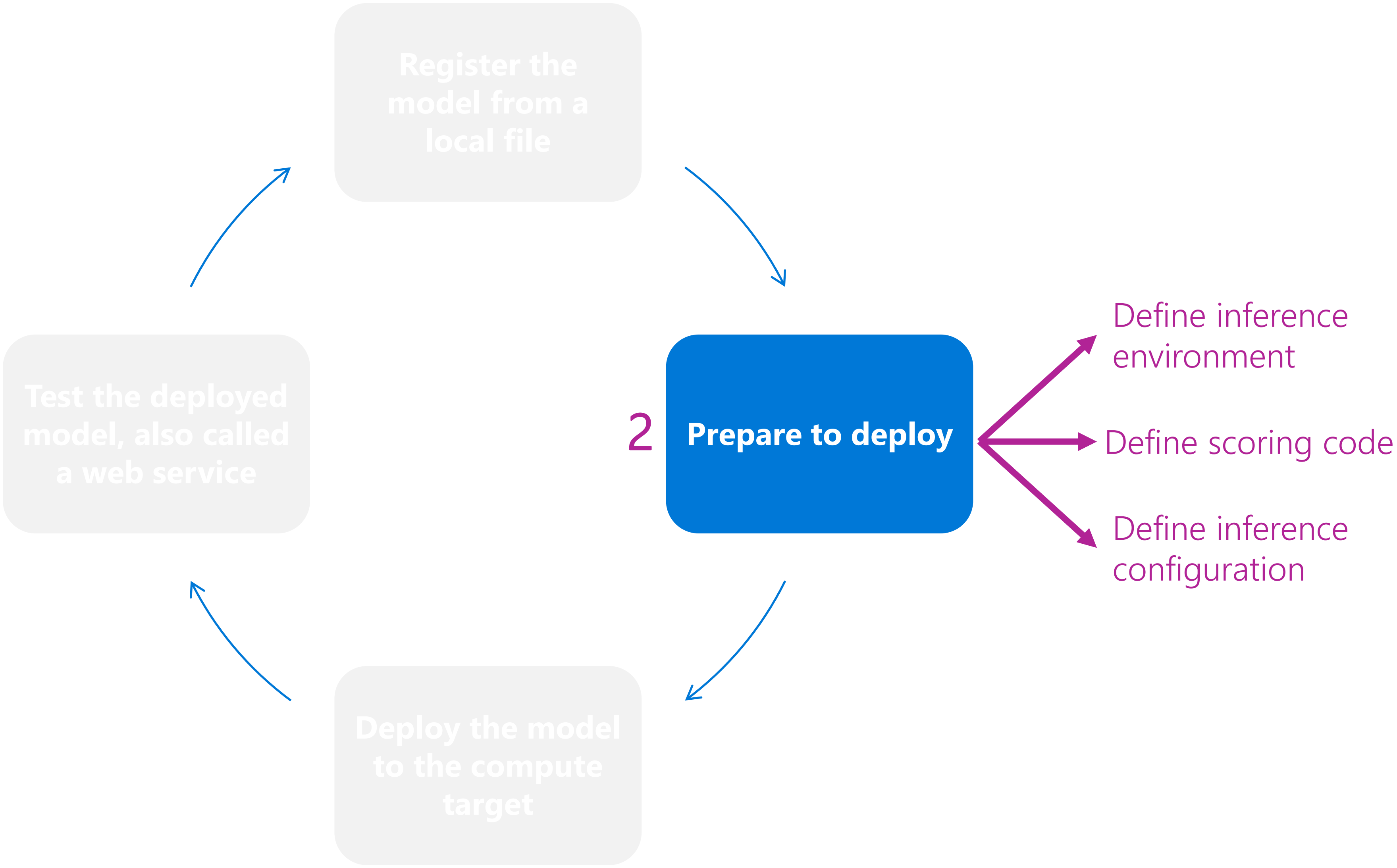

Register the model from a local file
2
Prepare to deploy
Define inference environment
Define scoring code
Define inference configuration
Deploy the model to the compute target
Test the deployed model, also called a web service

Step 2.1 – Prepare to Deploy: define inference environment

```
name: project_environment
dependencies:
  - python=3.6.2
  - scikit-learn=0.20.0
  - pip:
      # You must list azureml-defaults as a pip dependency
    - azureml-defaults>=1.0.45
    - inference-schema[numpy-support]
```

YAML file

```
from azureml.core.environment import Environment
myenv = Environment.from_conda_specification(name = 'myenv',
                                             file_path = 'path-to-conda-specification-file’)

myenv.register(workspace=ws)
```

Step 2.2 – Prepare to Deploy: define scoring code

init(): Typically, this function loads the model into a global object. This function is run only once, when the Docker container for your web service is started.

run(input_data): This function uses the model to predict a value based on the input data. Inputs and outputs of the run typically use JSON for serialization and deserialization. You can also work with raw binary data. You can transform the data before sending it to the model or before returning it to the client.

Load model files in your entry script

AZUREML_MODEL_DIR: An environment variable containing the path to the model location.

Model.get_model_path: An API that returns the path to model file using the registered model name.

Step 2.3 – Prepare to Deploy: define inference environment

```
from azureml.core.environment import Environment
from azureml.core.model import InferenceConfig


myenv = Environment.get(workspace=ws, name='myenv', version='1')
inference_config = InferenceConfig(entry_script='path-to-score.py',
                                   environment=myenv)
```

InferenceConfig class

- Represents configuration settings for a custom environment used for deployment.

- Inference configuration is an input parameter for Model deployment-related actions:
  - deploy(workspace, name, models, inference_config=None, deployment_config=None, deployment_target=None, overwrite=False)

  - profile(workspace, profile_name, models, inference_config, input_data=None, input_dataset=None, cpu=None, memory_in_gb=None, description=None)

  - package(workspace, models, inference_config=None, generate_dockerfile=False)

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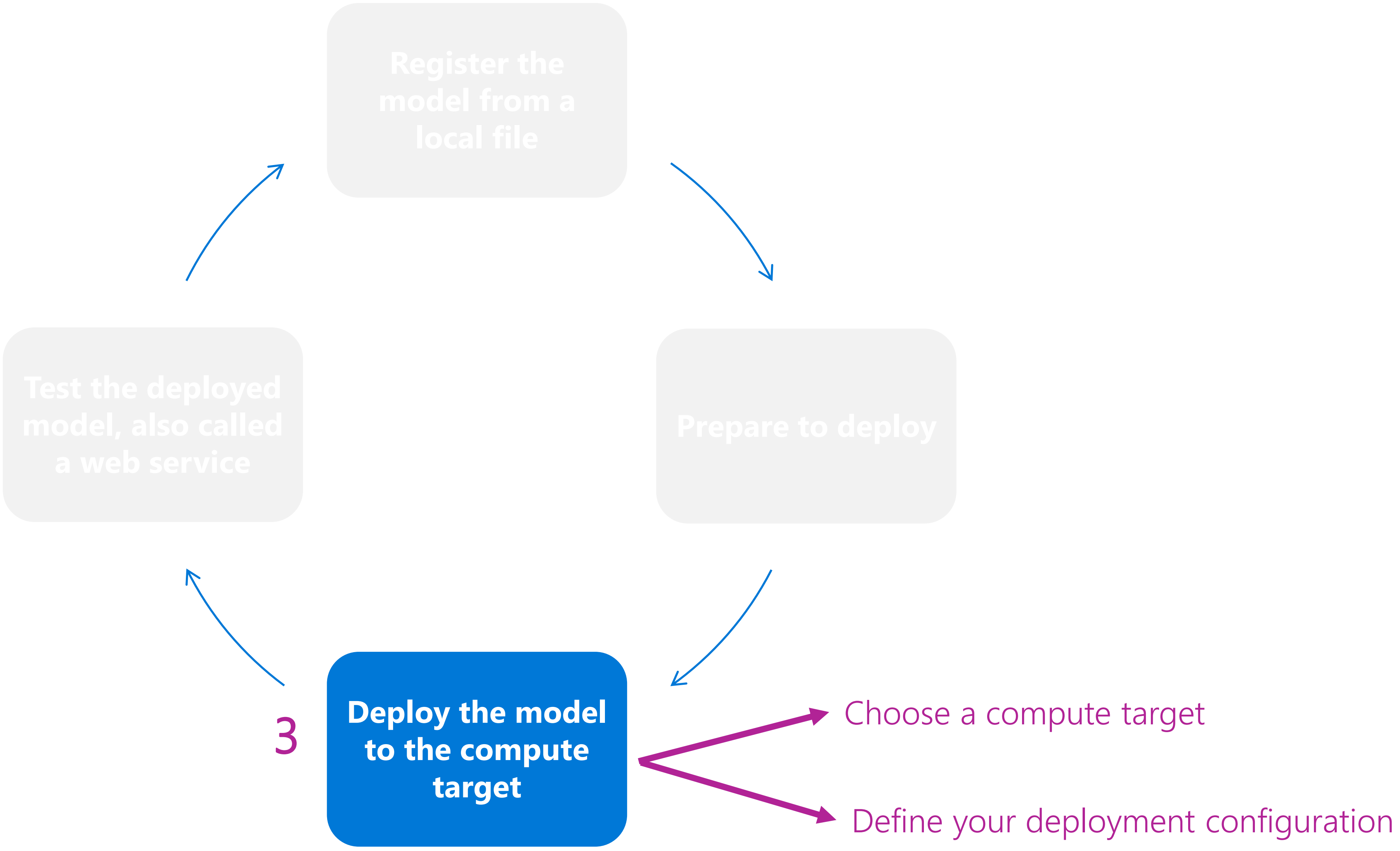
Register the model from a local file
Prepare to deploy
3
Deploy the model to the compute target
Test the deployed model, also called a web service
Choose a compute target
Define your deployment configuration

Step 3.1 – Deploy the model to the compute target: choose a compute target

Compute target	Used for	GPU support	FPGA support	Description
Local web service	Testing/debugging			Use for limited testing and troubleshooting. Hardware acceleration depends on use of libraries in the local system.
Azure Machine Learning compute instance web service	Testing/debugging			Use for limited testing and troubleshooting.
Azure Kubernetes Service (AKS)	Real-time inference	Yes (web service deployment)	Yes	Use for high-scale production deployments. Provides fast response time and autoscaling of the deployed service. Cluster autoscaling isn't supported through the Azure Machine Learning SDK. To change the nodes in the AKS cluster, use the UI for your AKS cluster in the Azure portal. AKS is the only option available for the designer.
Azure Container Instances	Testing or development			Use for low-scale CPU-based workloads that require less than 48 GB of RAM.
Azure Machine Learning compute clusters	(Preview) Batch inference	Yes (machine learning pipeline)		Run batch scoring on serverless compute. Supports normal and low-priority VMs.
Azure Functions	(Preview) Real-time inference			
Azure IoT Edge	(Preview) IoT module			Deploy and serve ML models on IoT devices.
Azure Data Box Edge	Via IoT Edge		Yes	Deploy and serve ML models on IoT devices.

Step 3.2 – Deploy the model to the compute target: define your deployment configuration

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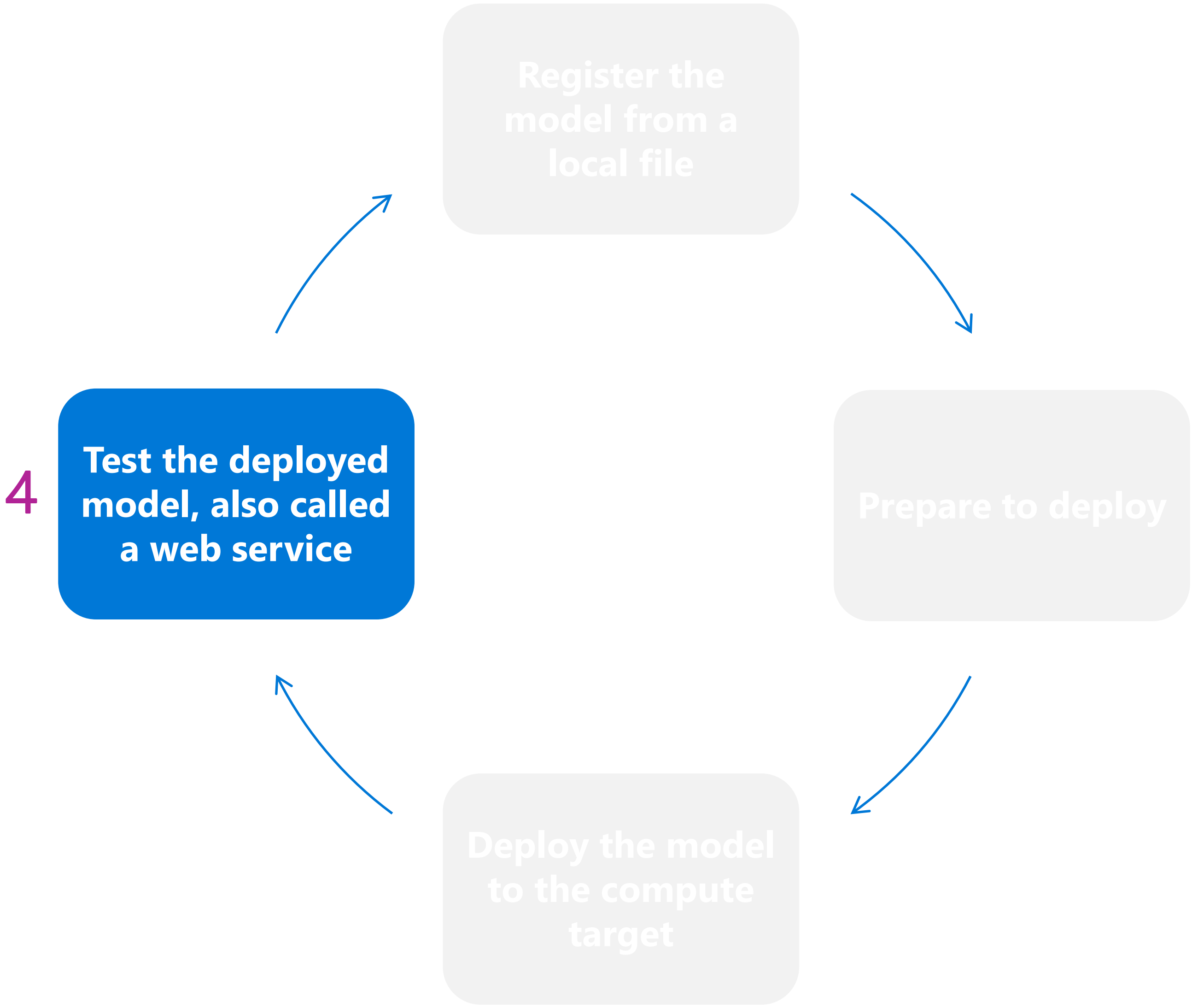
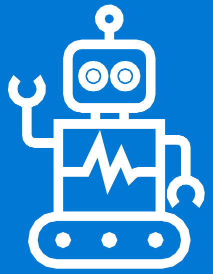
Compute target	Deployment configuration example
Local	`deployment_config = LocalWebservice.deploy_configuration(port=8890)`
Azure Container Instances	`deployment_config = AciWebservice.deploy_configuration(cpu_cores = 1, memory_gb = 1)`
Azure Kubernetes Service	`deployment_config = AksWebservice.deploy_configuration(cpu_cores = 1, memory_gb = 1)`

```
from azureml.core.webservice import AciWebservice, AksWebservice, LocalWebservice
```


Register the model from a local file
Prepare to deploy
Deploy the model to the compute target
4
Test the deployed model, also called a web service

Step 4 – Test the deployed model, also called a web service - Request-response consumption

```
import requests
import json

headers = {'Content-Type': 'application/json'}

if service.auth_enabled:
    headers['Authorization'] = 'Bearer '+service.get_keys()[0]
elif service.token_auth_enabled:
    headers['Authorization'] = 'Bearer '+service.get_token()[0]

print(headers)

test_sample = json.dumps({'data': [
    [1, 2, 3, 4, 5, 6, 7, 8, 9, 10],
    [10, 9, 8, 7, 6, 5, 4, 3, 2, 1]
]})

response = requests.post(
    service.scoring_uri, data=test_sample, headers=headers)
print(response.status_code)
print(response.elapsed)
print(response.json())
```



Automated Machine Learning 'simplifies' the creation and selection of the optimal model

Complexity of Machine Learning

www.aka.ms/algorithmcheatsheet

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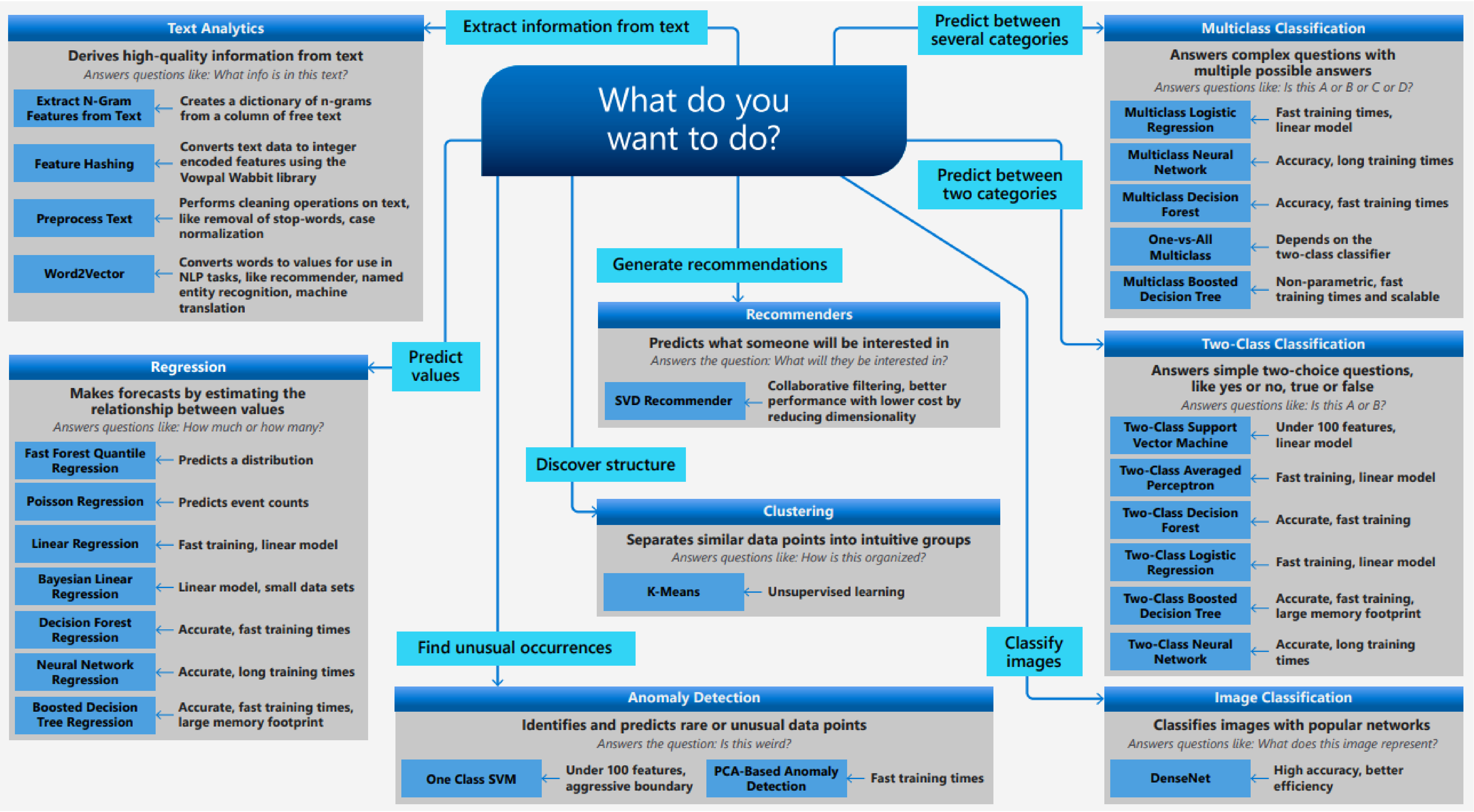
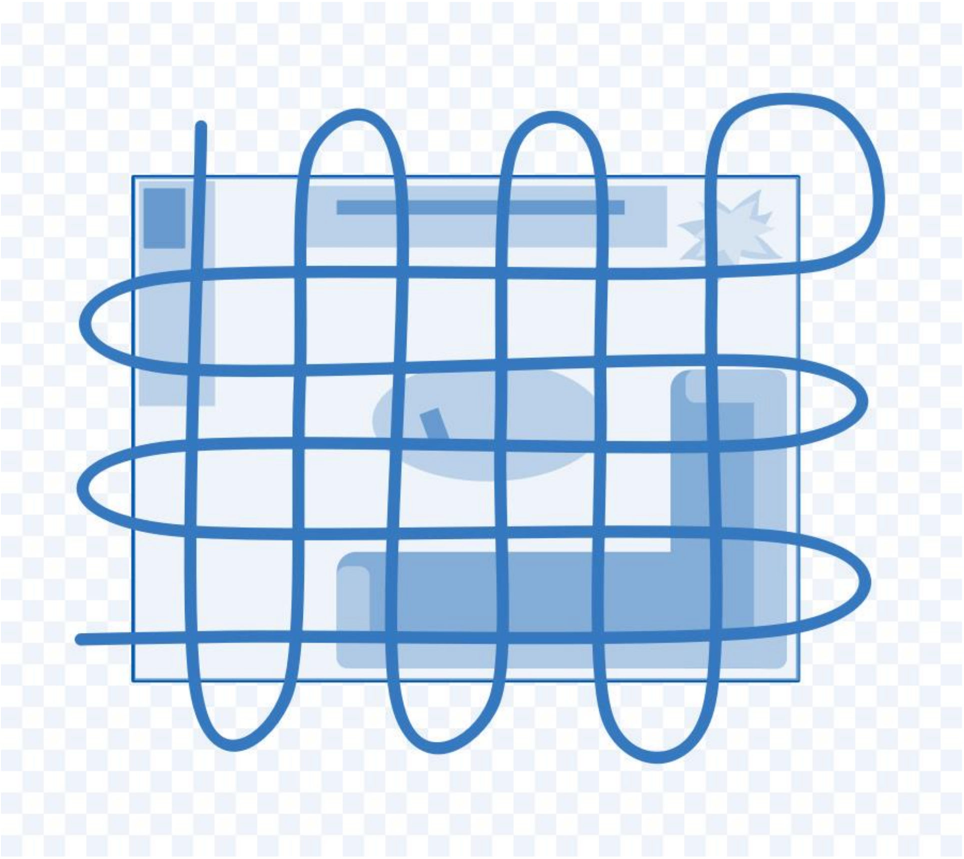


Challenges with Hyperparameter Selection

- The search space to explore—i.e. evaluating all possible combinations—is huge.
- Sparsity of good configurations.
  Very few of all possible configurations are optimal.
- Evaluating each configuration is resource and time consuming.
- Time and resources are limited.

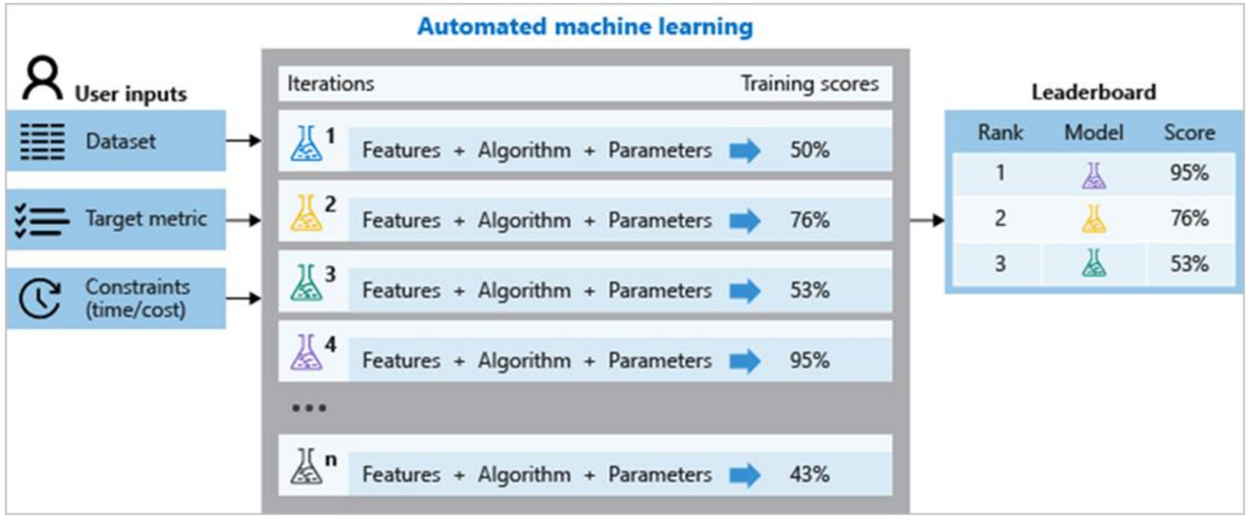


Automated Machine Learning

- Automated machine learning is the process of automating the time consuming, iterative tasks of **machine learning model development**.

- Data scientists, analysts and developers across industries can use automated ML to:
  - Implement machine learning solutions without extensive programming knowledge
  - Save time and resources
  - Leverage data science best practices
  - Provide agile problem-solving

How Automated ML works



1) Identify the ML problem to be solved: **classification**, **forecasting**, or **regression**

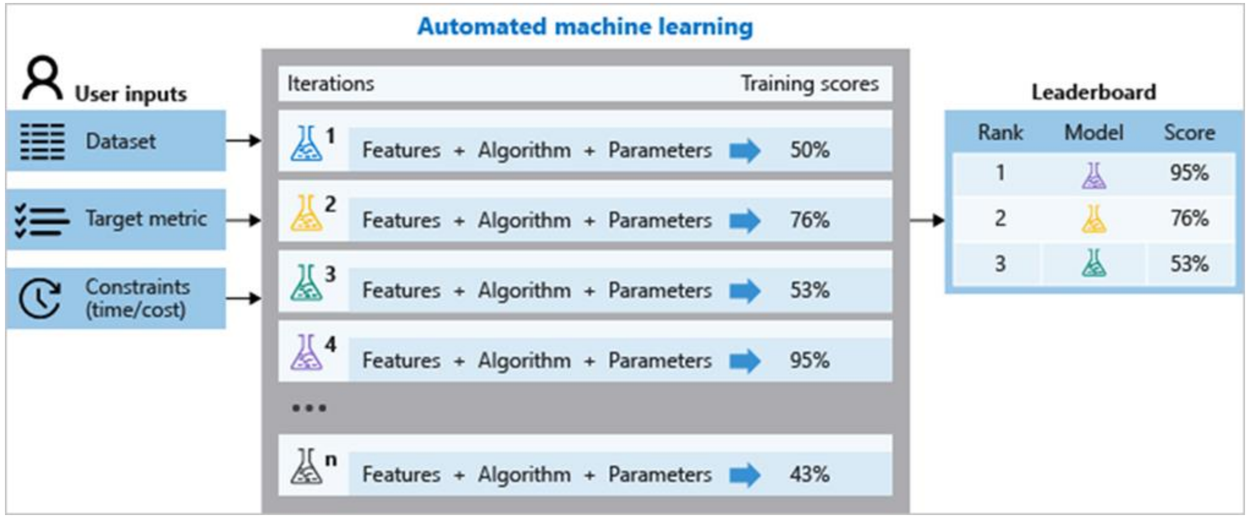
2) Specify the source and format of the labeled training data: **Numpy arrays** or **Pandas dataframe**

3) Configure the **compute target** for model training, such as your local computer, Azure Machine Learning Computes, remote VMs, or Azure Databricks

4) Configure the automated machine learning parameters that determine how many **iterations** over different models, **hyperparameter** settings, advanced **preprocessing/featurization**, and what **metrics** to look at when determining the best model

5) Submit the **training run**

How Automated ML works



- During training, the Azure Machine Learning service creates a number of in **parallel pipelines** that try different algorithms and parameters. It will stop once it hits the **exit criteria** defined in the experiment

- You can also inspect the **logged run information**, which contains metrics gathered during the run

- The training run produces a Python serialized object (**.pkl file**) that contains the model and data preprocessing

Automated and Interpretable ML →

- While model building is automated, **you can also learn how important or relevant features are to the generated models**

Demo

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Useful Resources:

- ✓ Azure MLOps: aka.ms/AMLOps
- ✓ AzureML GitHub: aka.ms/AzureMLGitHub
- ✓ Azure Machine Learning service: aka.ms/AzureMLservice
- ✓ Get started with Azure ML: aka.ms/GetStartedAzureML
- ✓ Automated Machine Learning Documentation: aka.ms/AutomatedMLDocs
- ✓ What is Automated Machine Learning? aka.ms/AutomatedML
- ✓ Model Interpretability with Azure ML Service: aka.ms/AzureMLModelInterpretability
- ✓ Algorithm Cheat Sheet: aka.ms/AlgorithmCheatSheet
- ✓ How to select Machine Learning algorithms: aka.ms/SelectAlgos
- ✓ Deep Learning vs Machine Learning: aka.ms/DeepLearningVSMachineLearning

Azure subscription

If anyone wants an Azure subscription linked to Princeton's Enterprise Enrollment, they should fill out the following form:

- https://princeton.service-now.com/service?id=sc_cat_item&sys_id=06268c7c1bc444d098d1217e6e4bcb4f

They will need to supply a Princeton account chart string for billing.

Please reach out to Princeton OIT, Mark Ratliff, with questions.

Thanks!

Thank you!

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