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DeepLearning.AI

Neural Architecture Search

Welcome

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Neural Architecture Search

Hyperparameter tuning

Neural Architecture Search

- Neural architecture search (NAS) is is a technique for automating the design of artificial neural networks
- It helps finding the optimal architecture
- This is a search over a huge space
- AutoML is an algorithm to automate this search

Types of parameters in ML Models

- Trainable parameters:
  - Learned by the algorithm during training
  - e.g. weights of a neural network

- Hyperparameters:
  - set before launching the learning process
  - not updated in each training step
  - e.g: learning rate or the number of units in a dense layer

Manual hyperparameter tuning is not scalable

- Hyperparameters can be numerous even for small models
- e.g shallow DNN:
    - Architecture choices
    - activation functions
    - Weight initialization strategy
    - Optimization hyperparameters such as learning rate, stop condition
- Tuning them manually can be a real brain teaser
- Tuning helps with model performance

Automating hyperparameter tuning with Keras Tuner

- Automation is key: open source resources to the rescue
- Keras Tuner:
  - Hyperparameter tuning with Tensorflow 2.0.
  - Many methods available

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Neural Architecture Search

Keras Autotuner Demo

Setting up libraries and dataset

```
import tensorflow as tf
from tensorflow import keras
mnist = tf.keras.datasets.mnist


(x_train, y_train),(x_test, y_test) = mnist.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0
```

Deep learning "Hello world!"

```
model = tf.keras.models.Sequential([
  tf.keras.layers.Flatten(input_shape=(28, 28)),
  tf.keras.layers.Dense(512, activation='relu'),
  tf.keras.layers.Dropout(0.2),
  tf.keras.layers.Dense(10, activation='softmax')
])

model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

model.fit(x_train, y_train, epochs=5)
model.evaluate(x_test, y_test)
```

Model performance

```
Epoch 1/5
1875/1875 - 10s 5ms/step - loss: 0.3603 - accuracy: 0.8939
Epoch 2/5
1875/1875 - 10s 5ms/step - loss: 0.1001 - accuracy: 0.9695
Epoch 3/5
1875/1875 - 10s 5ms/step - loss: 0.0717 - accuracy: 0.9781
Epoch 4/5
1875/1875 - 10s 5ms/step - loss: 0.0515 - accuracy: 0.9841
Epoch 5/5
1875/1875 - 10s 5ms/step - loss: 0.0432 - accuracy: 0.9866
```

Parameters rational: if any

```
model = tf.keras.models.Sequential([
  tf.keras.layers.Flatten(input_shape=(28, 28)),
  tf.keras.layers.Dense(512, activation='relu'),
  tf.keras.layers.Dropout(0.2),
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model.evaluate(x_test, y_test)
```

Is this architecture optimal?

- Do the model need more or less hidden units to perform well?
- How does model size affect the convergence speed?
- Is there any trade off between convergence speed, model size and accuracy?
- Search automation is the natural path to take
- Keras tuner built in search functionality.

Automated search with Keras tuner

```
# First, install Keras Tuner

!pip install -q -U keras-tuner


# Import Keras Tuner after it has been installed

import kerastuner as kt
```

Building model with iterative search

```
def model_builder(hp):
  model = keras.Sequential()
  model.add(keras.layers.Flatten(input_shape=(28, 28)))

  hp_units = hp.Int('units', min_value=16, max_value=512, step=16)
  model.add(keras.layers.Dense(units=hp_units, activation='relu'))
  model.add(tf.keras.layers.Dropout(0.2))
  model.add(keras.layers.Dense(10))

  model.compile(optimizer='adam',loss='sparse_categorical_crossentropy',
    metrics=['accuracy'])
  return model
```

Search strategy

```
tuner = kt.Hyperband(model_builder,
                     objective='val_accuracy',
                     max_epochs=10,
                     factor=3,
                     directory='my_dir',
                     project_name='intro_to_kt')


  Other flavors: RandomSearch // BayesianOptimization // Sklearn
```

Callback configuration

```
stop_early =
    tf.keras.callbacks.EarlyStopping(monitor='val_loss',
                                     patience=5)


tuner.search(x_train,
             y_train,
             epochs=50,
             validation_split=0.2,
             callbacks=[stop_early])
```

Search output

```
Trial 24 Complete [00h 00m 22s]
val_accuracy: 0.3265833258628845
Best val_accuracy So Far: 0.5167499780654907
Total elapsed time: 00h 05m 05s
Search: Running Trial #25
Hyperparameter    |Value              |Best Value So Far
units             |192                |48
tuner/epochs      |10                 |2
tuner/initial_e...|4                  |0
tuner/bracket     |1                  |2
tuner/round       |1                  |0
tuner/trial_id    |a2edc917bda476c...|None
```

Back to your model

```
model = tf.keras.models.Sequential([
  tf.keras.layers.Flatten(input_shape=(28, 28)),
  tf.keras.layers.Dense(48, activation='relu'),
  tf.keras.layers.Dropout(0.2),
  tf.keras.layers.Dense(10, activation='softmax')
])
```

Training output

```
Epoch 1/5
1875/1875 - 3s 1ms/step - loss: 0.6427 - accuracy: 0.8090
Epoch 2/5
1875/1875 - 3s 1ms/step - loss: 0.2330 - accuracy: 0.9324
Epoch 3/5
1875/1875 - 3s 1ms/step - loss: 0.1835 - accuracy: 0.9448
Epoch 4/5
1875/1875 - 3s 1ms/step - loss: 0.1565 - accuracy: 0.9515
Epoch 5/5
1875/1875 - 3s 1ms/step - loss: 0.1393 - accuracy: 0.9564
```

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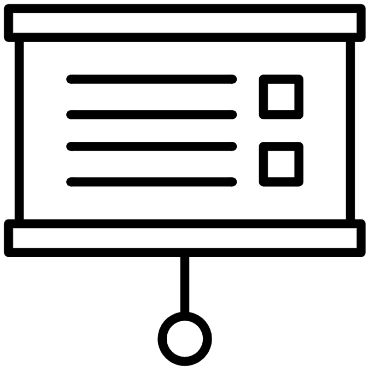
AutoML

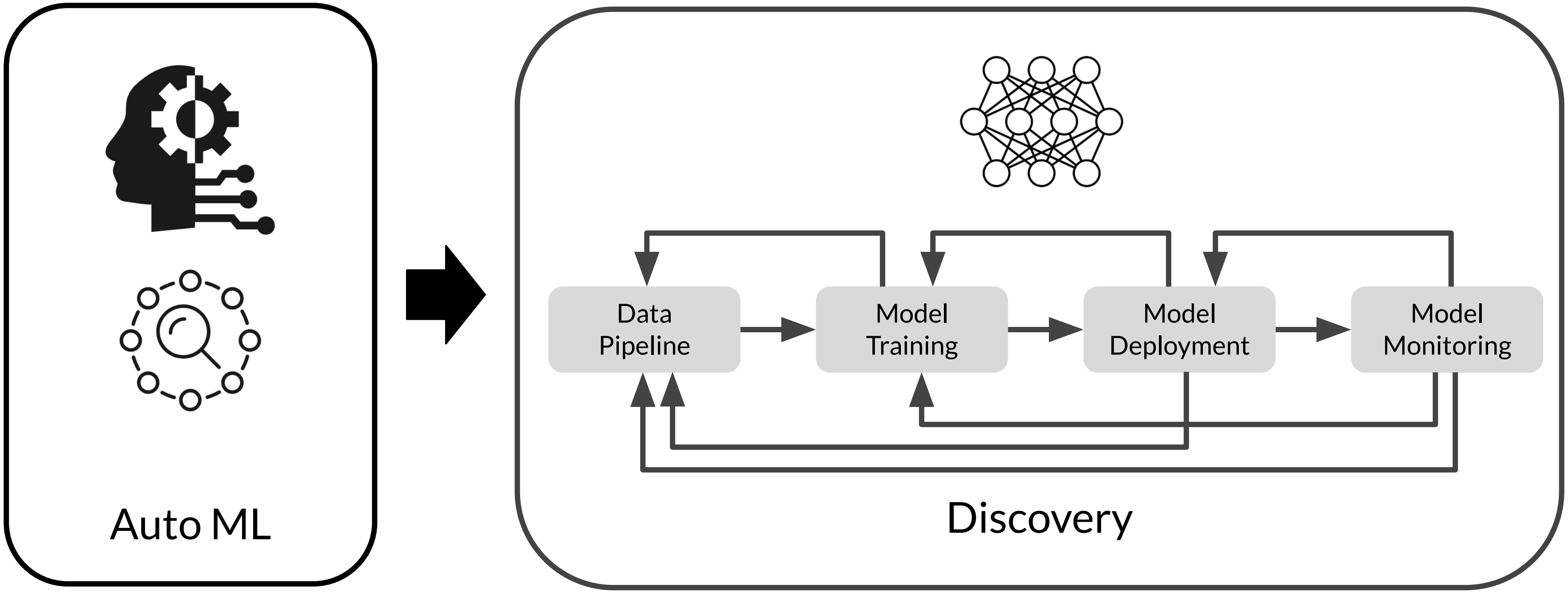
Intro to AutoML

Outline

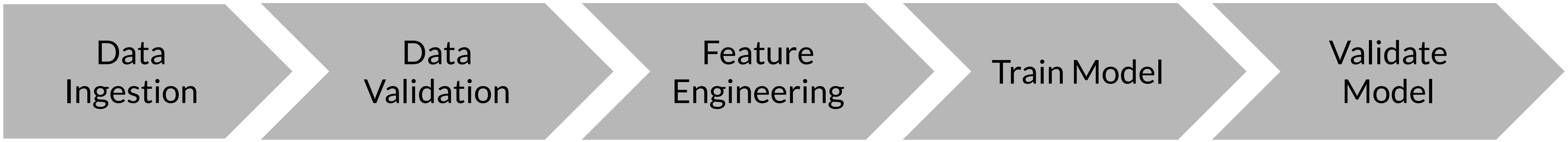
- Introduction to AutoML
- Neural Architecture Search
- Search Space and Search Strategies
- Performance Estimation
- AutoML on the Cloud



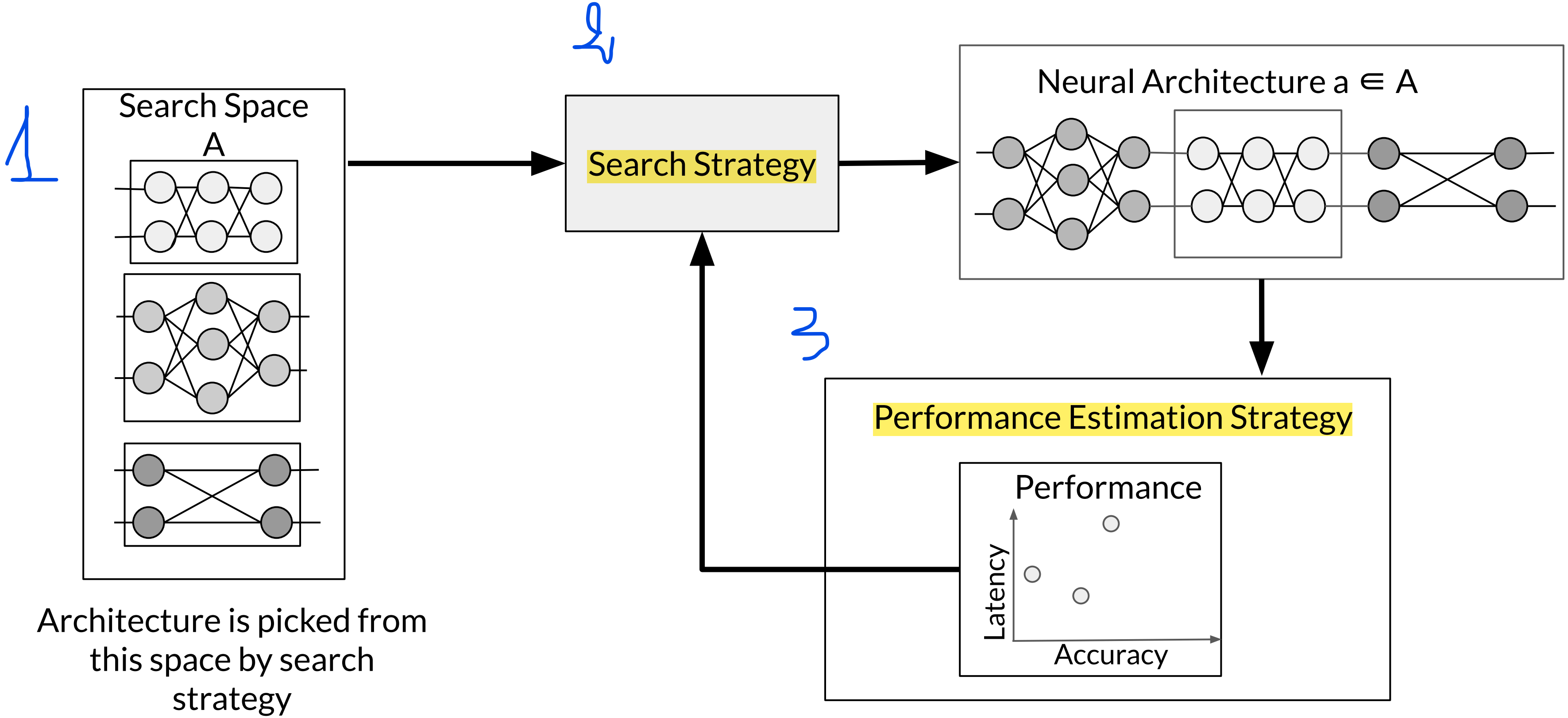
Automated Machine Learning (AutoML)



AutoML automates the entire ML workflow

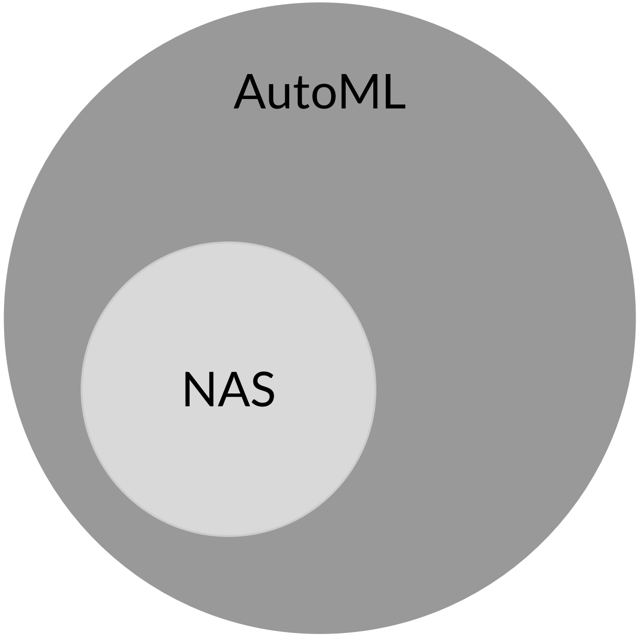


Neural Architecture Search

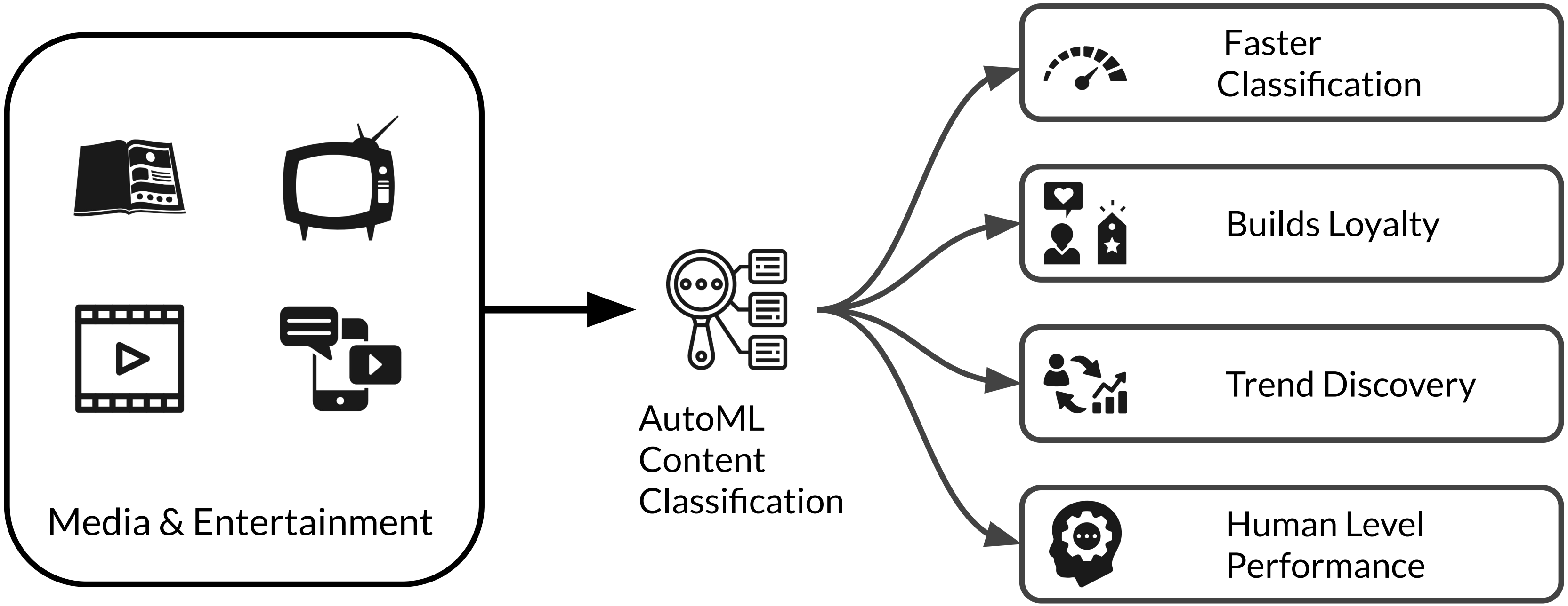


Neural Architecture Search

- **AutoML** automates the development of ML models
- **AutoML** is not specific to a particular type of model.
- Neural Architecture Search (**NAS**) is a subfield of AutoML
- NAS is a technique for automating the design of artificial neural networks (ANN).



Real-World example: Meredith Digital



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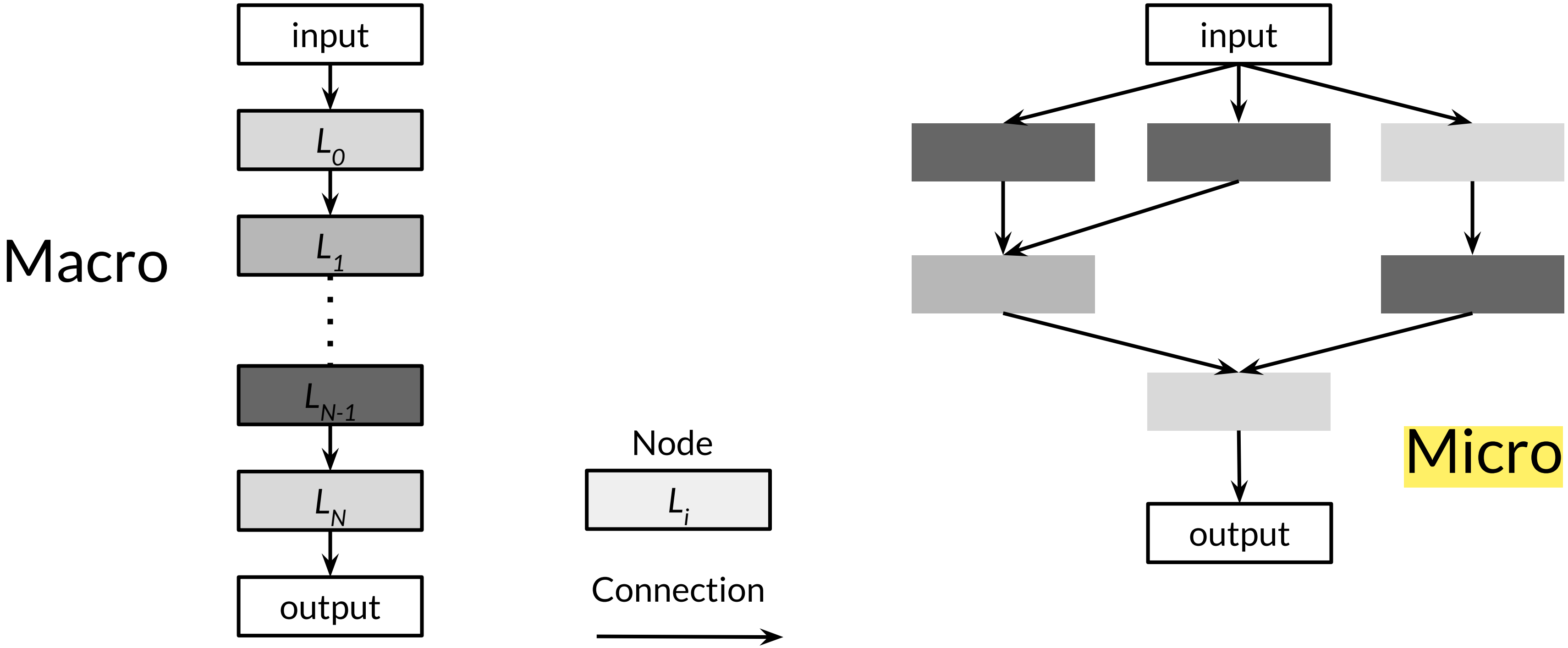
AutoML

Understanding Search Spaces

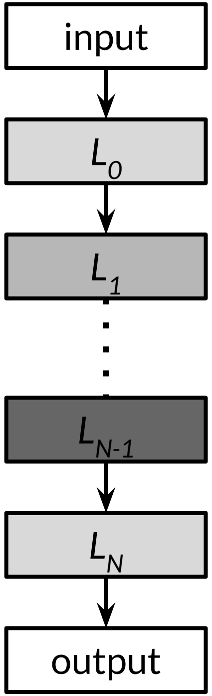
Types of Search Spaces



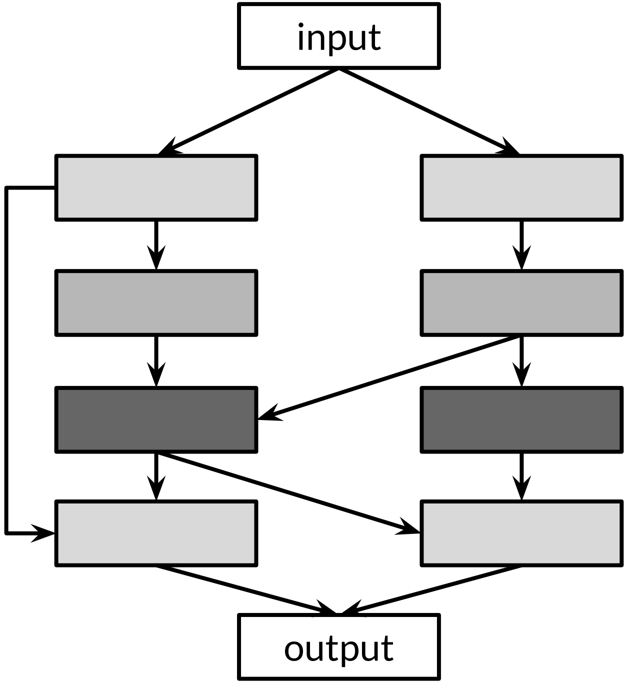
Macro Architecture Search Space

Contains individual layers and connection types

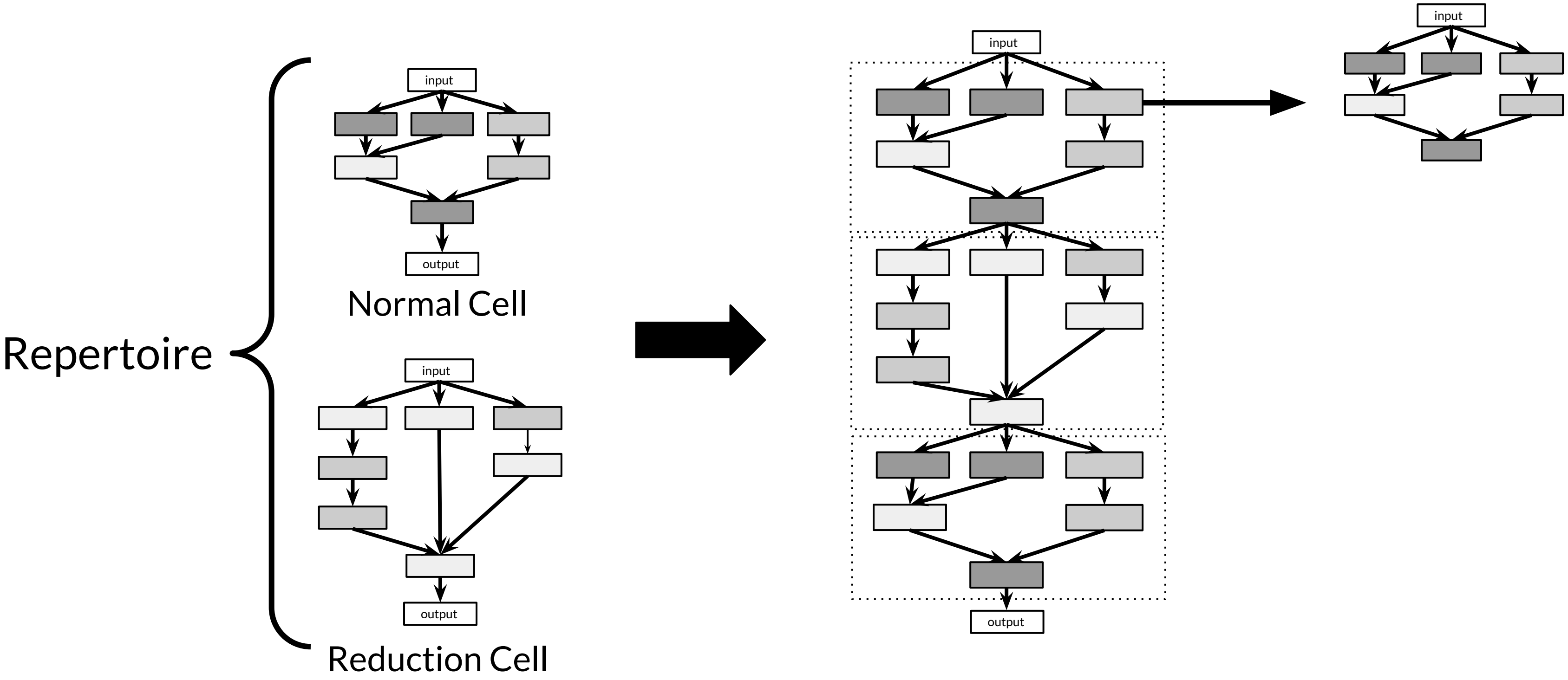
Chain structured space



Complex search space



Micro Architecture Search Space



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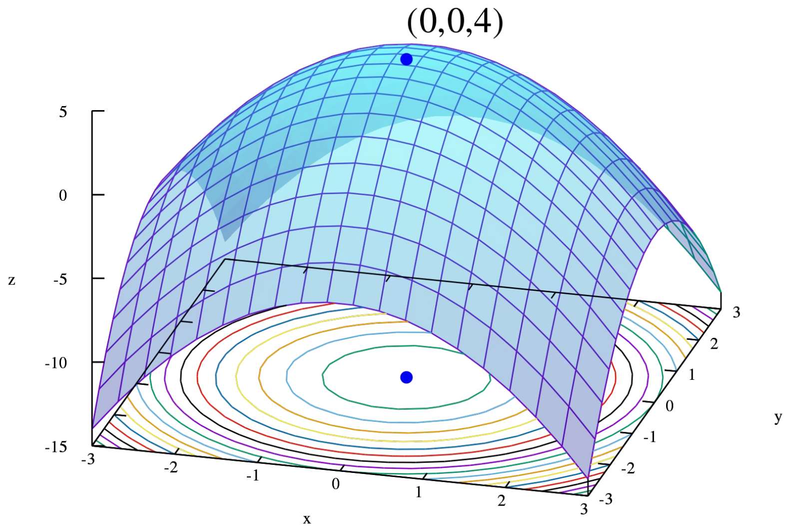
Search Strategies

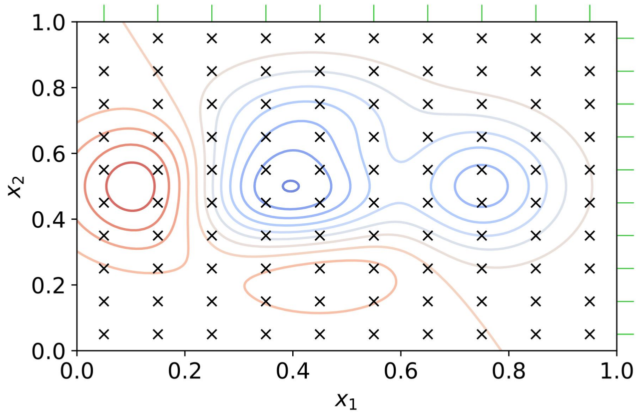
A Few Search Strategies

1. Grid Search
2. Random Search
3. Bayesian Optimization
4. Evolutionary Algorithms
5. Reinforcement Learning



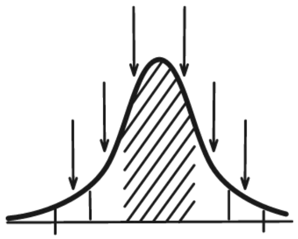
Grid Search and Random Search

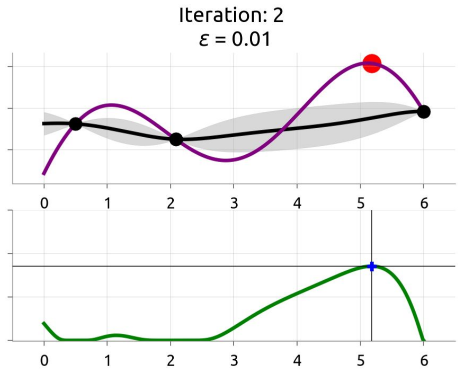
- Grid Search
  - Exhaustive search approach on fixed grid values
- Random Search
- Both suited for smaller search spaces.
- Both quickly fail with growing size of search space.



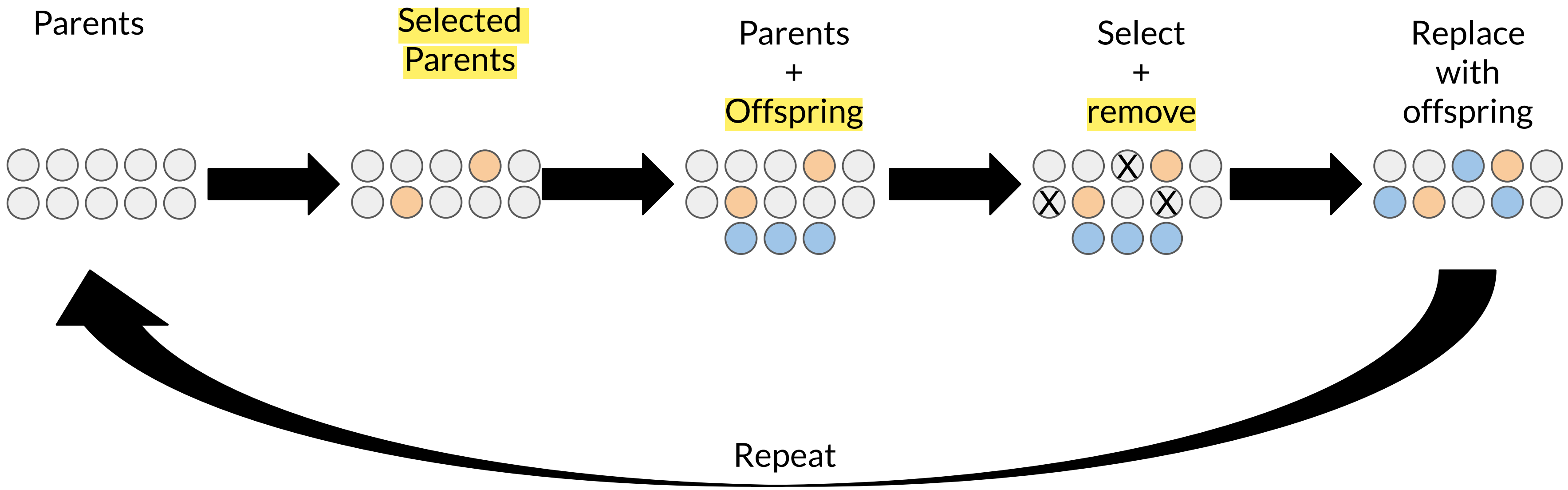
Bayesian Optimization

- Assumes that a *specific probability distribution*, is underlying the performance.
- Tested architectures constrain the probability distribution and guide the selection of the next option.
- In this way, promising architectures can be stochastically determined and tested.



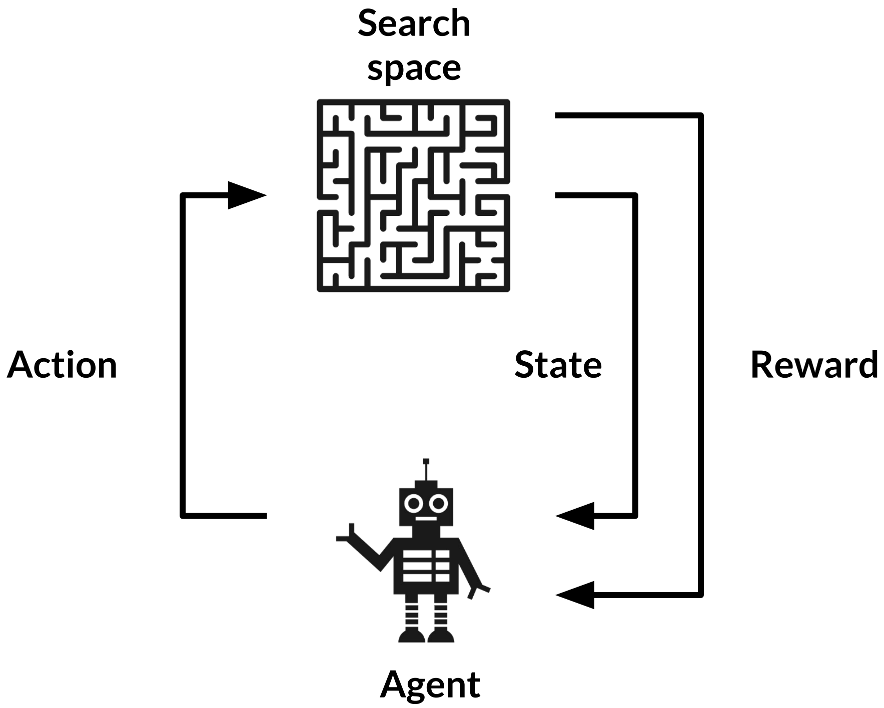


Evolutionary Methods

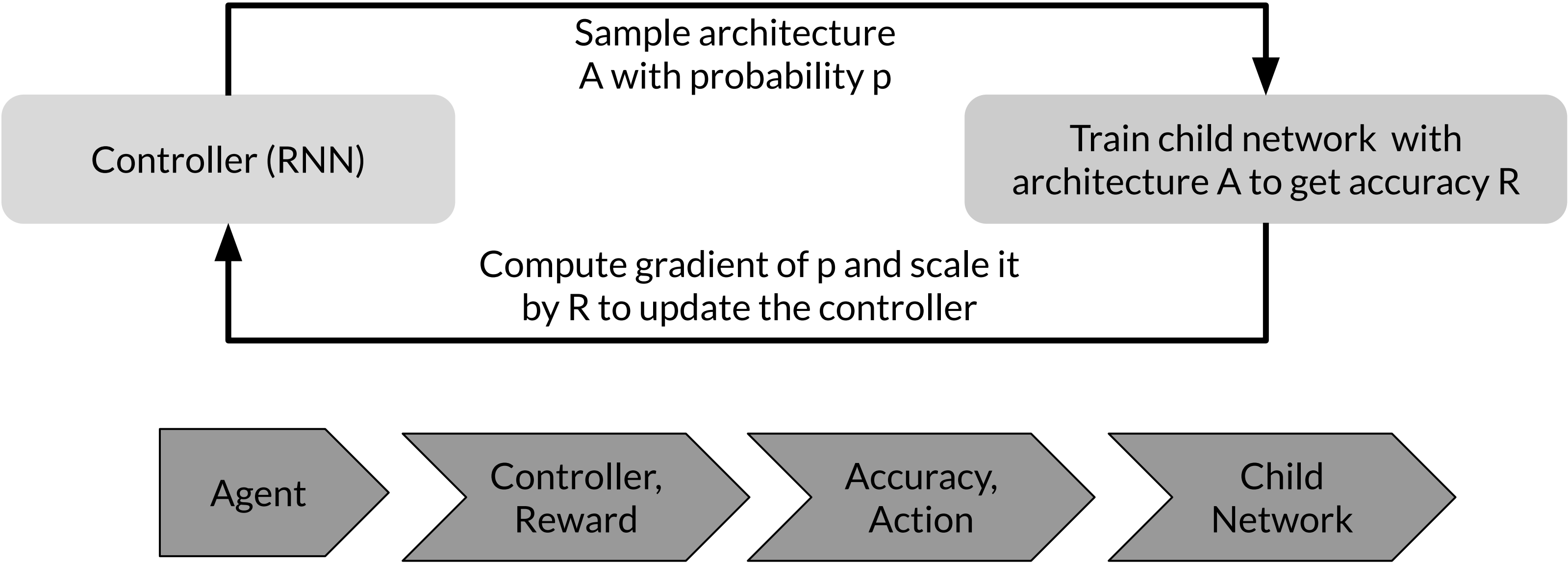


Reinforcement Learning

- Agents goal is to maximize a reward
- The available options are selected from the search space
- The performance estimation strategy determines the reward



Reinforcement Learning for NAS



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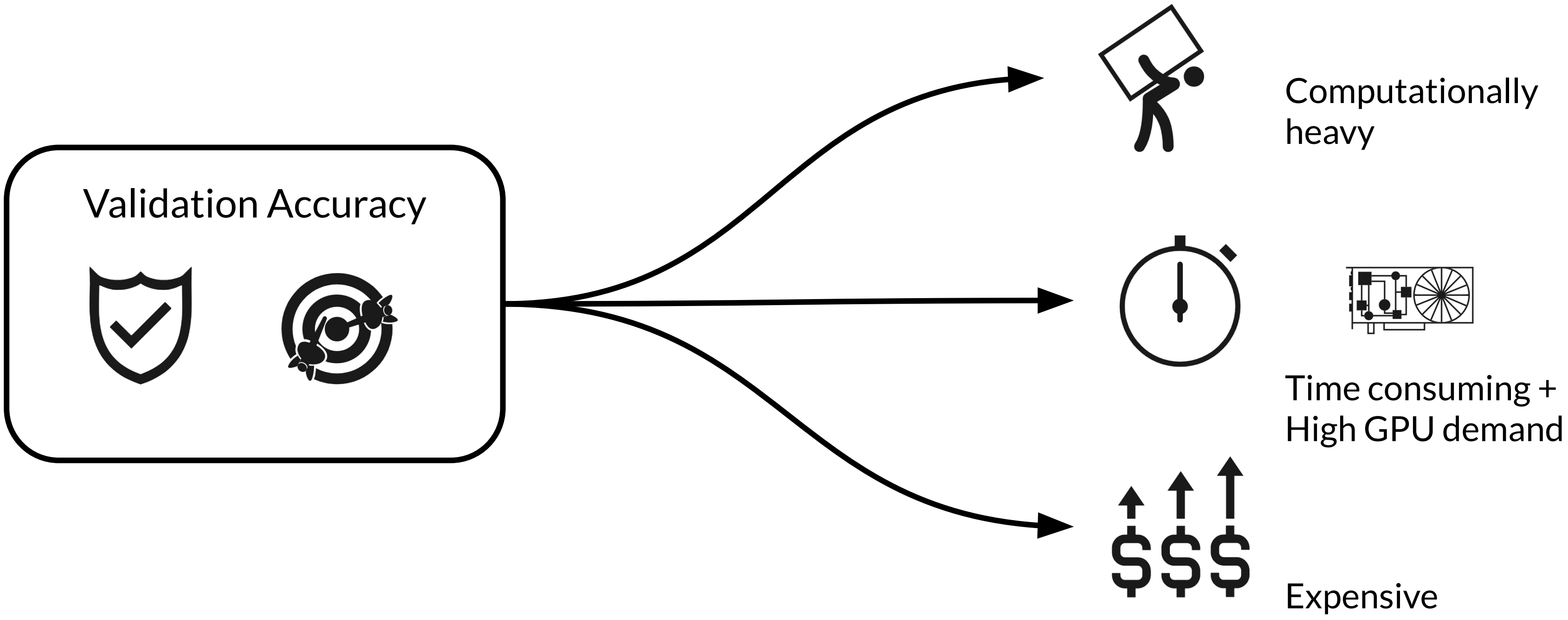
Measuring AutoML Efficacy

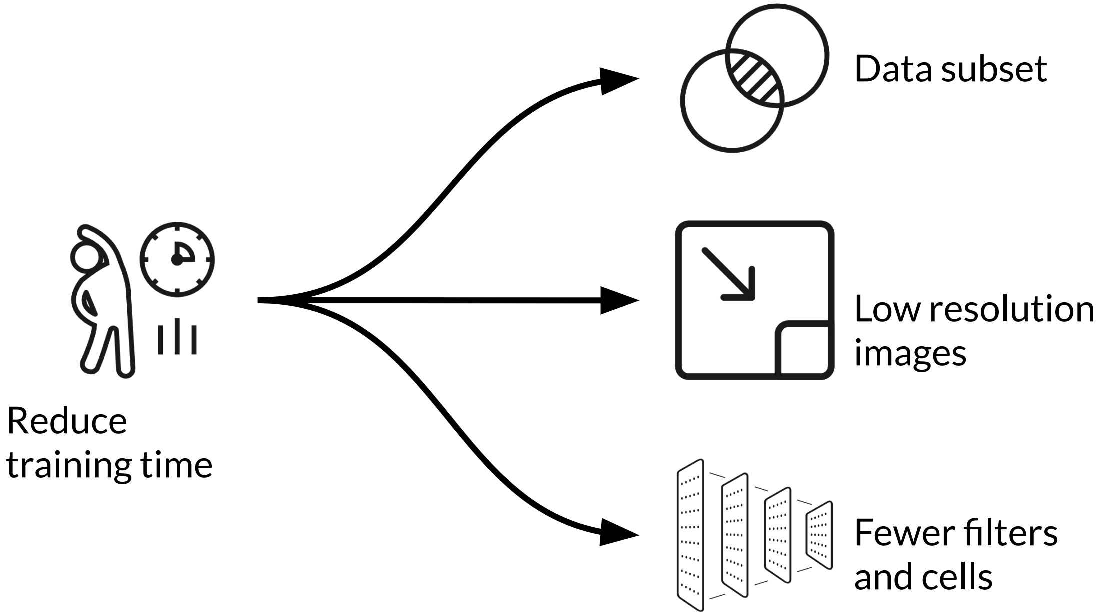
Performance Estimation Strategy



Strategies to Reduce the Cost

1. Lower fidelity estimates
2. Learning Curve Extrapolation
3. Weight Inheritance/ Network Morphisms

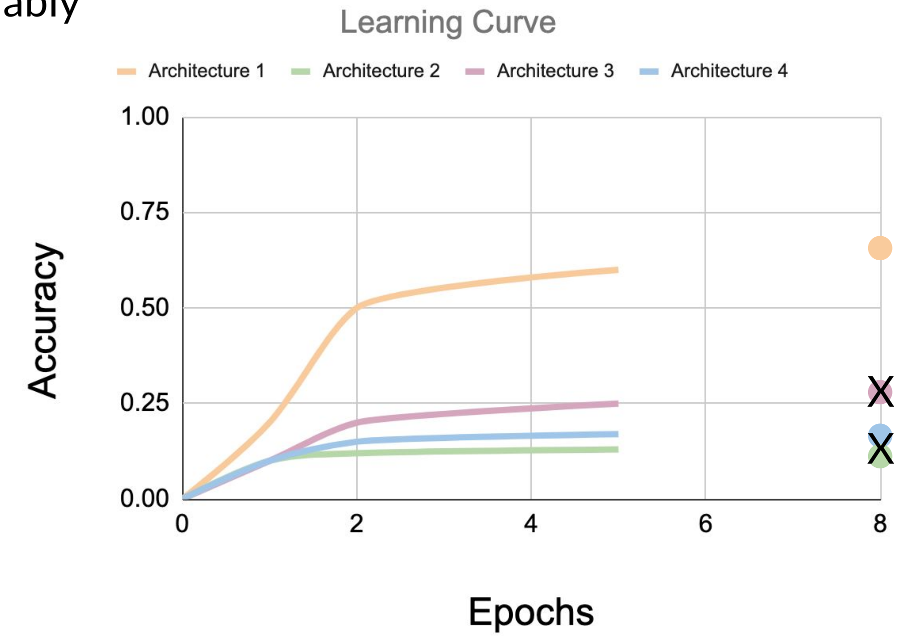
Lower Fidelity Estimates



- Reduce cost but underestimates performance
- Works if **relative ranking** of architectures does not change due to lower fidelity estimates
- Recent research shows this is not the case

Learning Curve Extrapolation

- Requires predicting the learning curve reliably
- Extrapolates based on initial learning.
- Removes poor performers



Weight Inheritance/Network Morphisms

- Initialize weights of new architectures based on previously trained architectures
    - Similar to transfer learning
- Uses **Network Morphism**
- Underlying function unchanged
    - New network inherits knowledge from parent network.
    - Computational speed up: only a few days of GPU usage
    - Network size not inherently bounded

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AutoML

AutoML on the Cloud

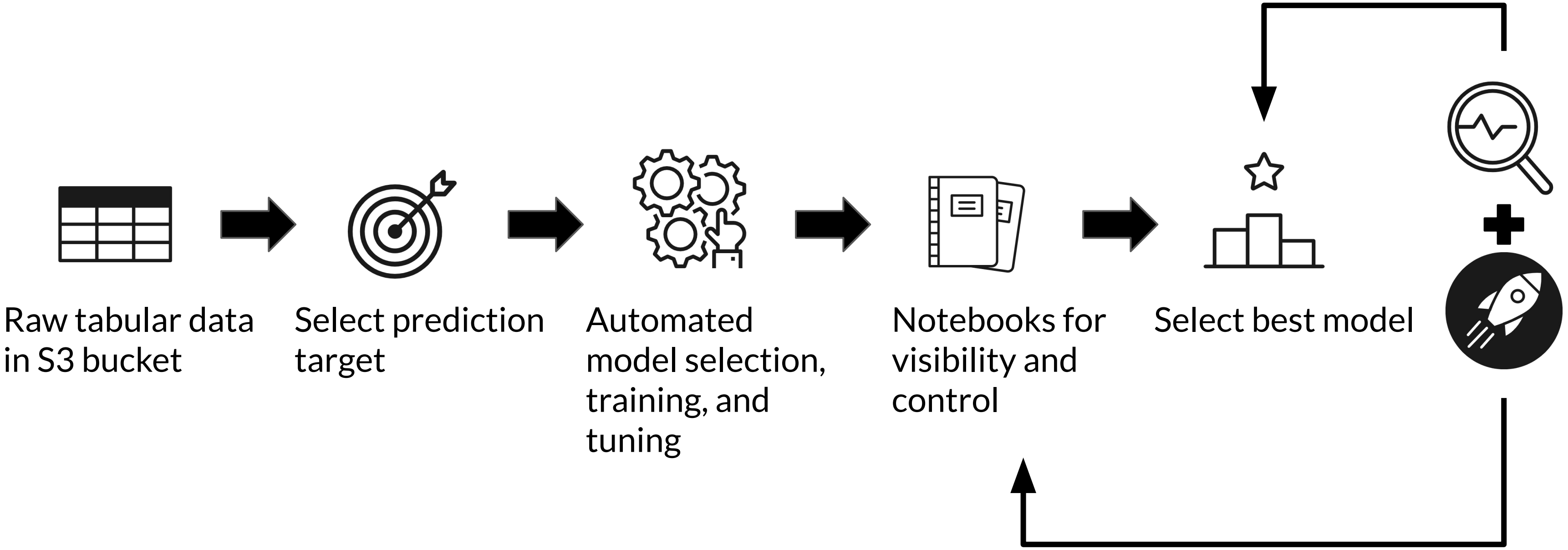
Popular Cloud Offerings

Cloud-based AutoML

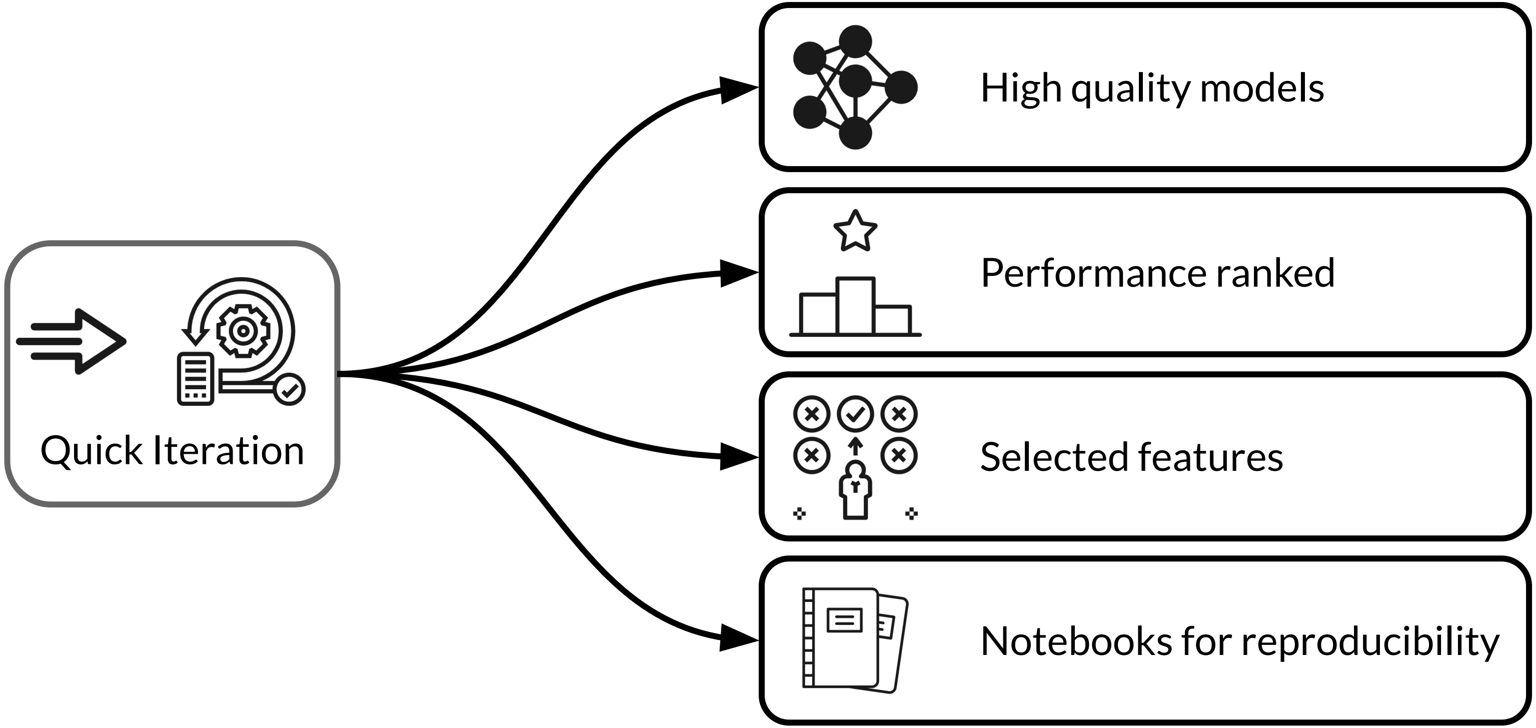
- Amazon SageMaker Autopilot
- Microsoft Azure Automated Machine Learning
- Google Cloud AutoML

Amazon SageMaker Autopilot

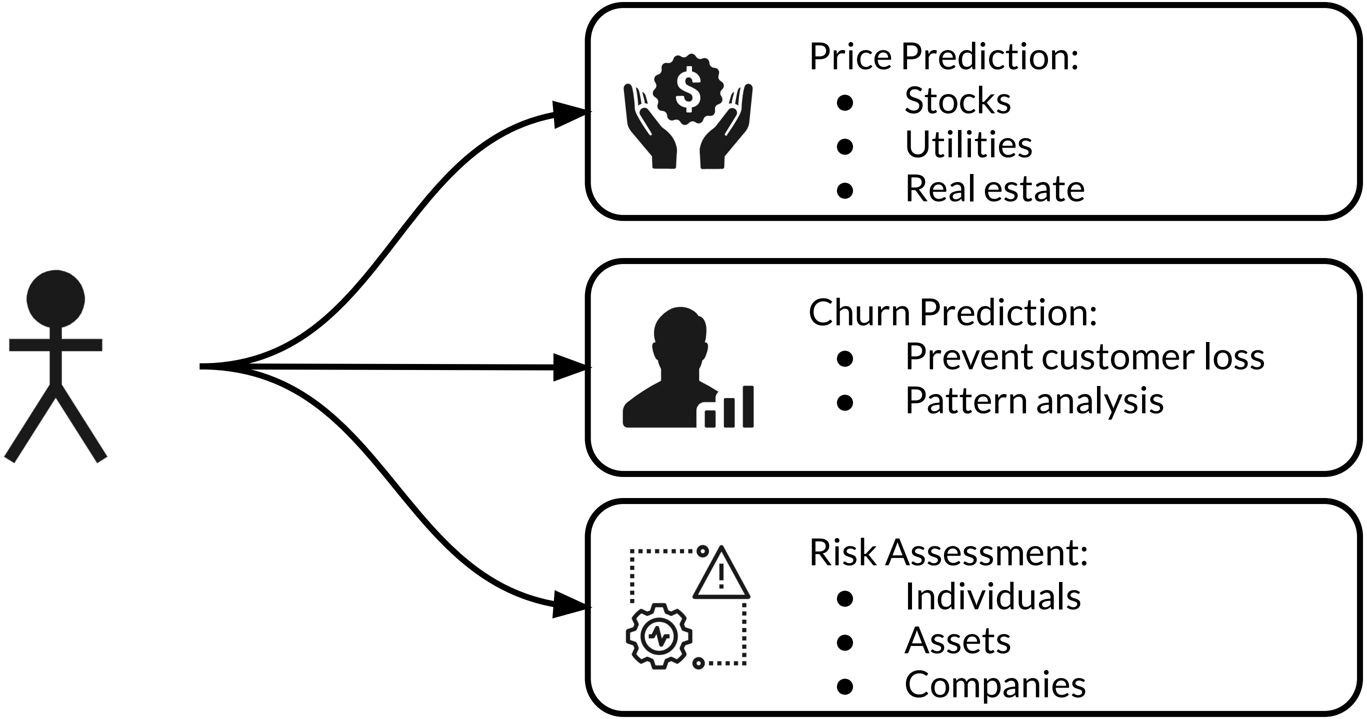
Amazon SageMaker Autopilot



Key features

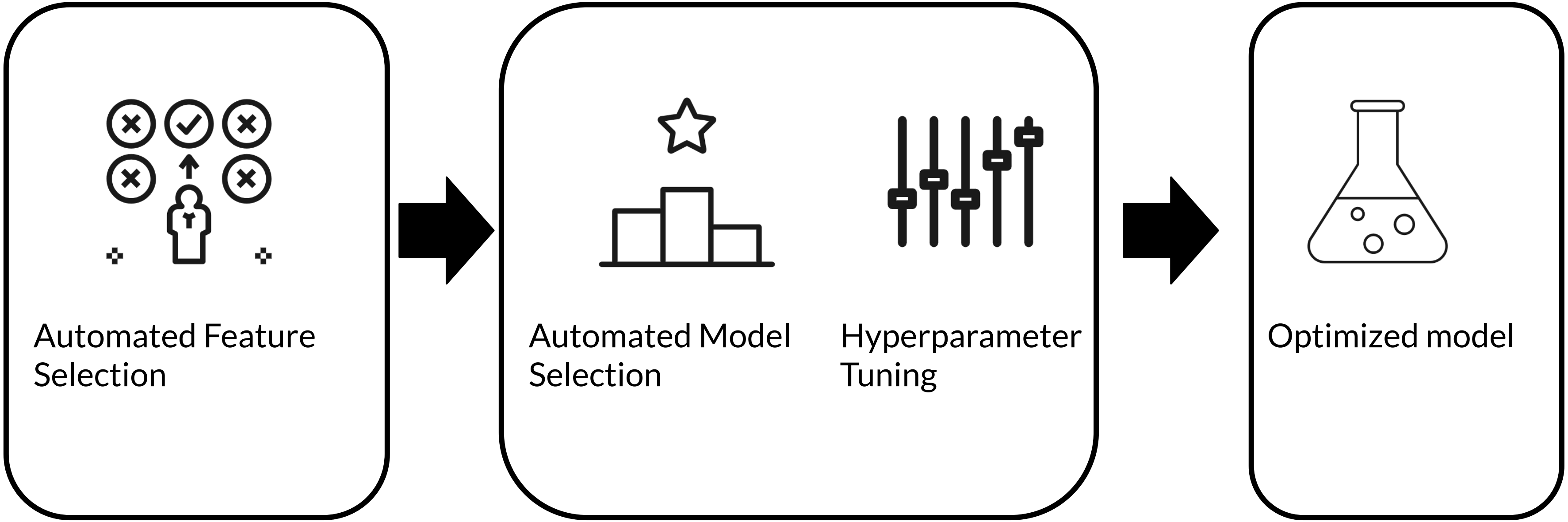


Typical use cases



Microsoft Azure
Automated Machine Learning

Microsoft Azure AutoML



Key features

Quick customization:
- Model
- Control settings

Automated Feature Engineering

Data Visualization

Intelligent stopping

Key features

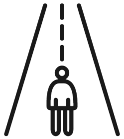
- Experiment summaries
- Metric visualizations

Model Interpretability

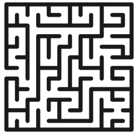
Pattern Discovery

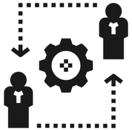
Google Cloud AutoML

Google Cloud AutoML



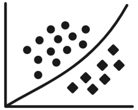
- Accessible to beginners
- Train high-quality models





- Neural Architecture Search
- Transfer Learning

- GUI Based
- Pipeline life-cycle



- Data labeling
- Data cleaning

Cloud AutoML Products

Sight	Auto ML Vision Derive insights from images in the cloud or at the edge.	Auto ML Video Intelligence Enable powerful content discovery and engaging video experiences.
Language	AutoML Natural Language Reveal the structure and meaning of text through machine learning.	Auto ML Translation Dynamically detect and translate between languages.
Structured Data	AutoML Tables Automatically build and deploy state-of-the-art machine learning models on structured data.	

AutoML Vision Products

Auto ML Vision Classification	AutoML Vision Edge Image Classification
AutoML Vision Object Detection	AutoML Vision Edge Object Detection

AutoML Video Intelligence Products

AutoML Video Intelligence Classification

Enables you to train machine learning models, to classify shots and segments on your videos according to your own defined labels.

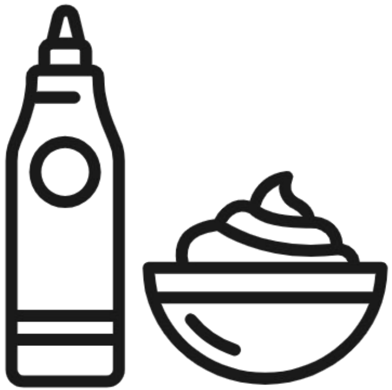
AutoML Video Object detection

Enables you to train machine learning models to detect and track multiple objects, in shots and segments.

So what's in the secret sauce?

How do these Cloud offerings perform AutoML?

- We don't know (or can't say) and they're not about to tell us
- The underlying algorithms will be similar to what we've learned
- The algorithms will evolve with the state of the art



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AutoML

Assignment Setup

Steps to Classify Images using AutoML Vision

1 → 2 → 3 → 4 → 5 → 6

1. Setup AutoML

2. Create Dataset

Upload images to Cloud Storage and create dataset in Vision.

3. Train

4. Evaluate

5. Deploy

Deploy model for serving

6. Test

Generate predictions using deployed model

QWIKLABS

1 → 2 → 3 → 4 → 5 → 6

1. Setup AutoML
2. Create Dataset
3. Train
4. Evaluate
5. Deploy
6. Test

- **Qwiklabs** provides real cloud environments that help developers and IT professionals learn cloud platforms and software.
- Check tutorial on **Qwiklabs** basics

It's your turn!