# ML Modeling Pipelines in Production

## Part 1: Neural Architecture Search

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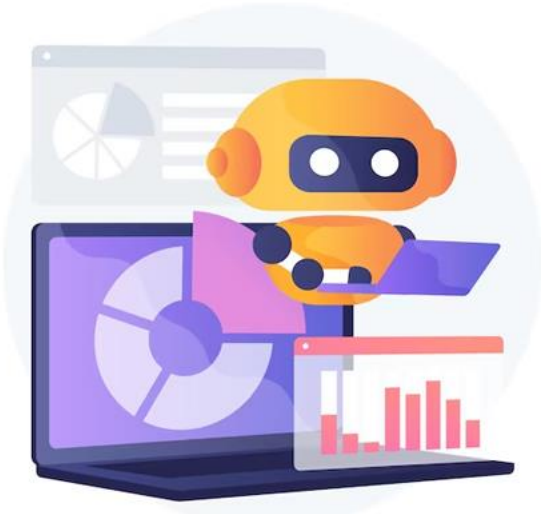
# Neural Architecture Search

- Neural architecture search (NAS) 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



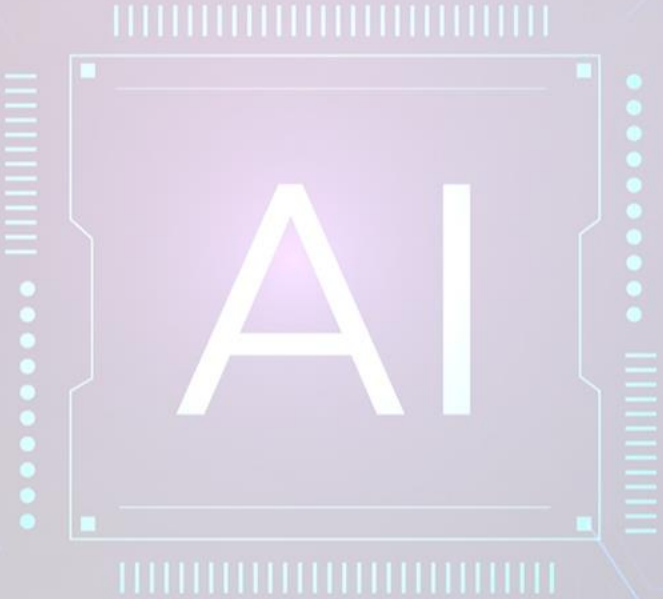
# Manual hyperparameter tuning is not scalable

- 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

# Example



# 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
```

# Model performance

```
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)
```

# 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'))

  odel.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,
             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
```

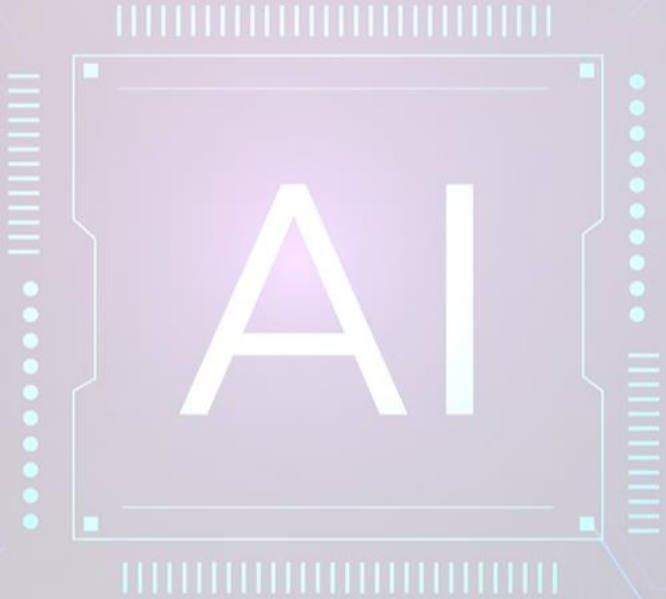
# Back to your model

```
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')
])
```

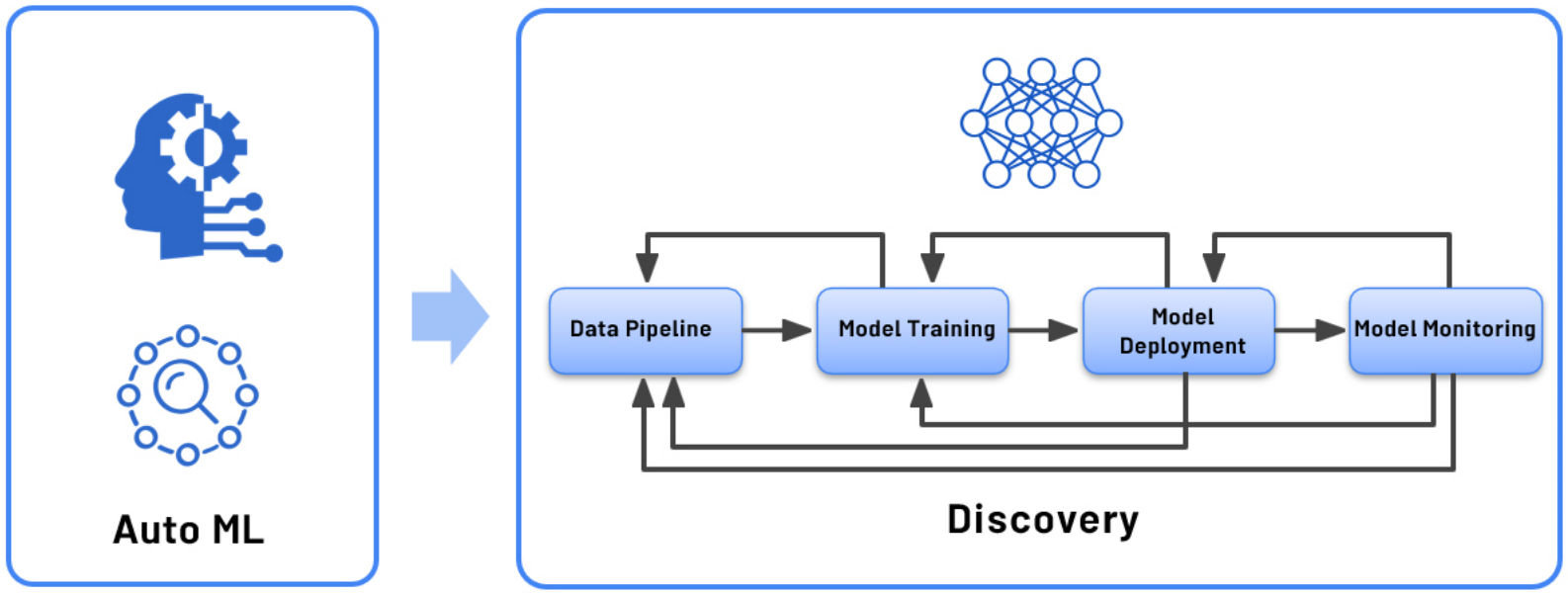
# Training Output

```
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
```

# AutoML

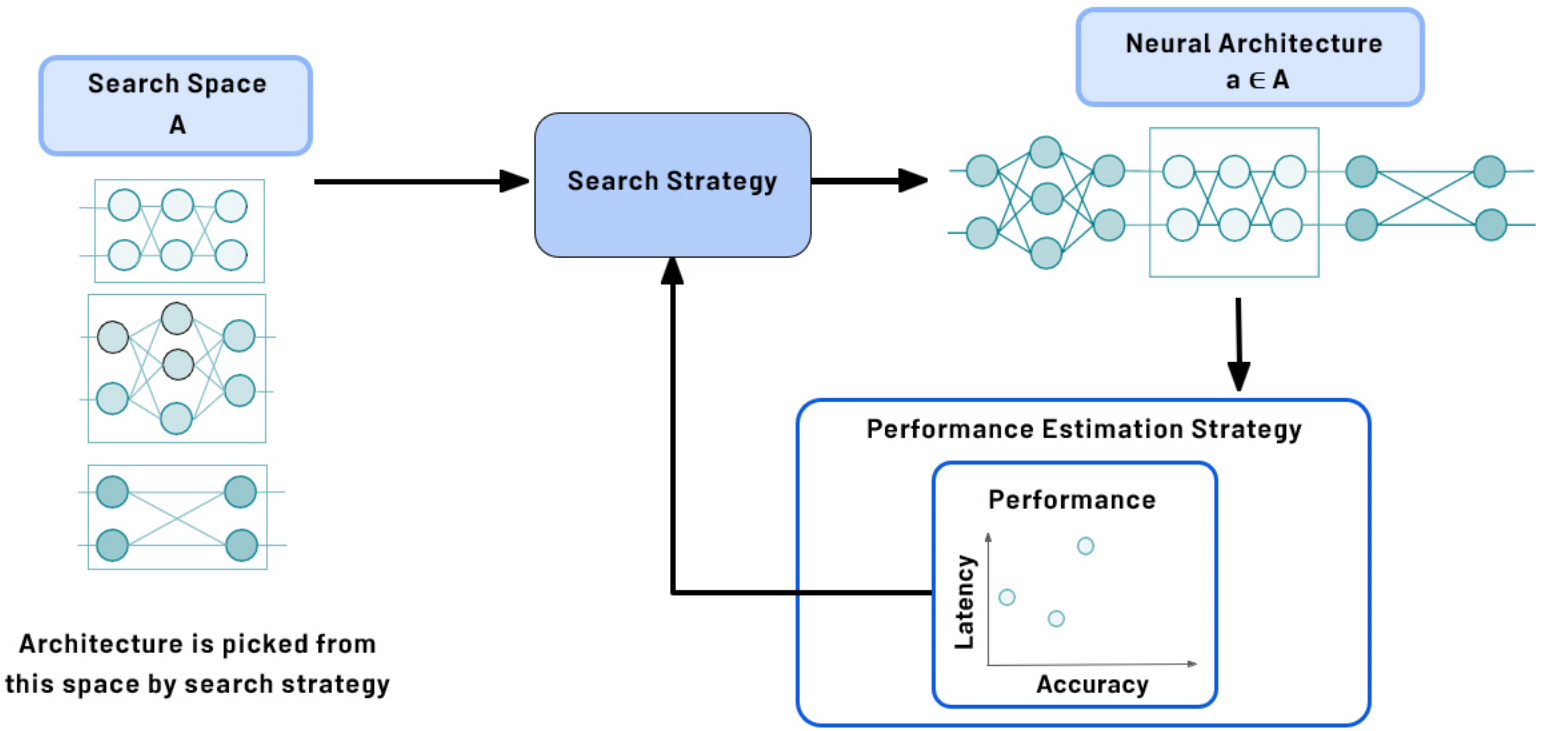


# Automated Machine Learning (AutoML)



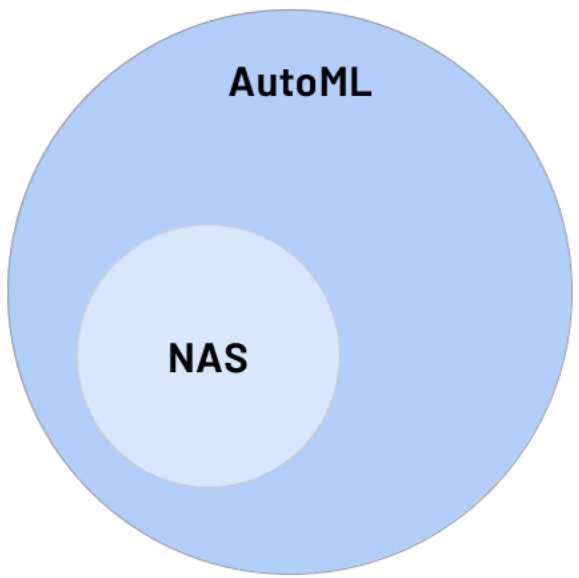
# AutoML automates the entire ML workflow

# Neural architecture search

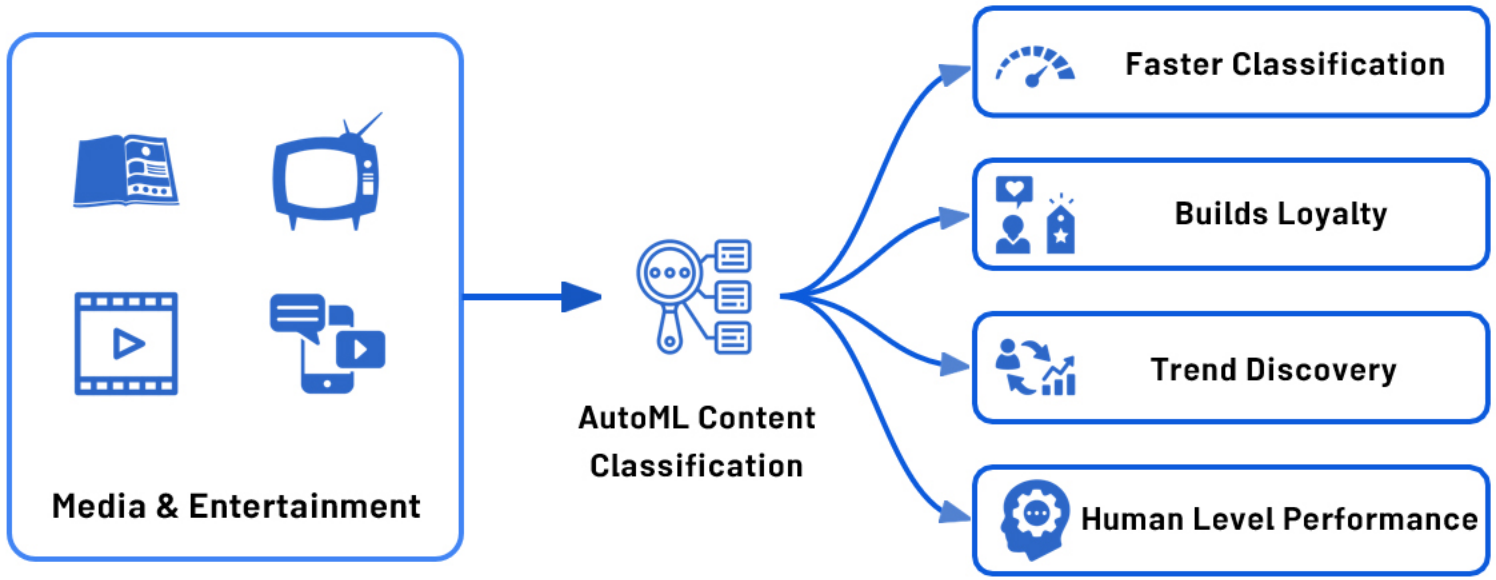


# Neural architecture search

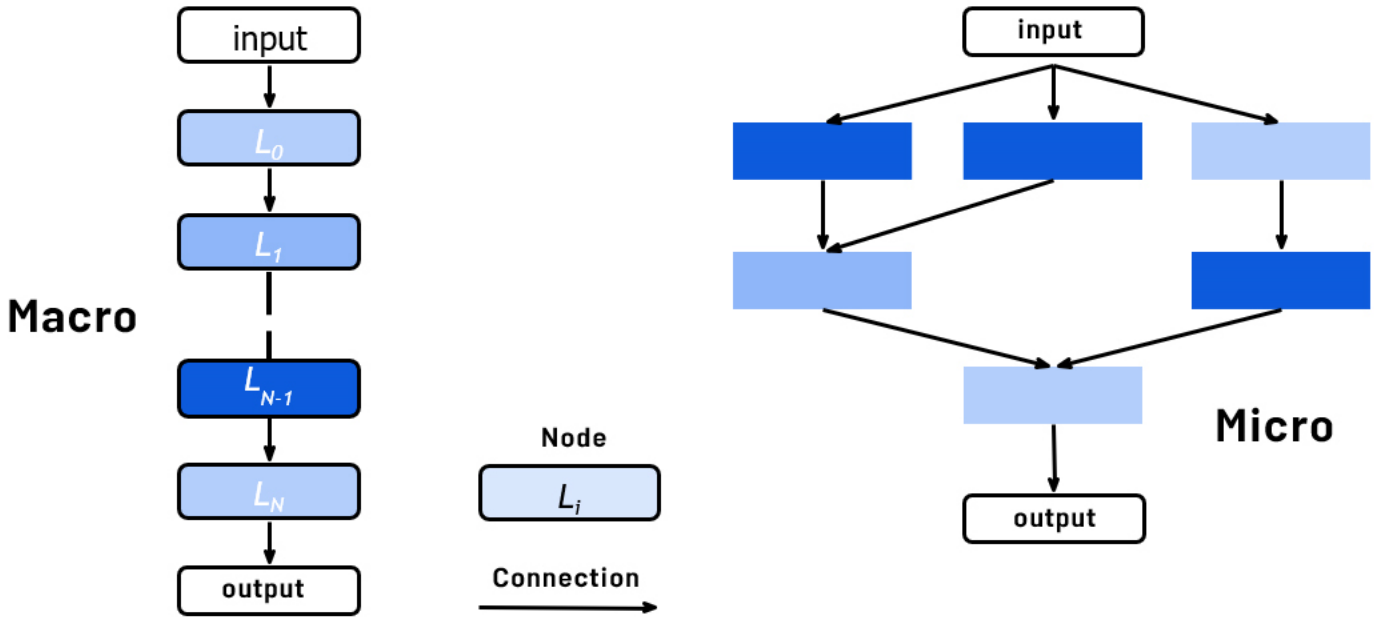
- **AutoML** automates the development of ML models.
- **AutoML** is not specific to a particular type of model.
- Neural Architecture Search (**NAS**) is a subfield of AutoML.
- NAS is a technique for automating the design of artificial neural networks (ANN).



# Real-World example: Meredith Digital



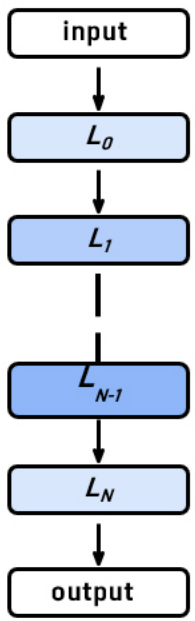
# Types of Search Spaces



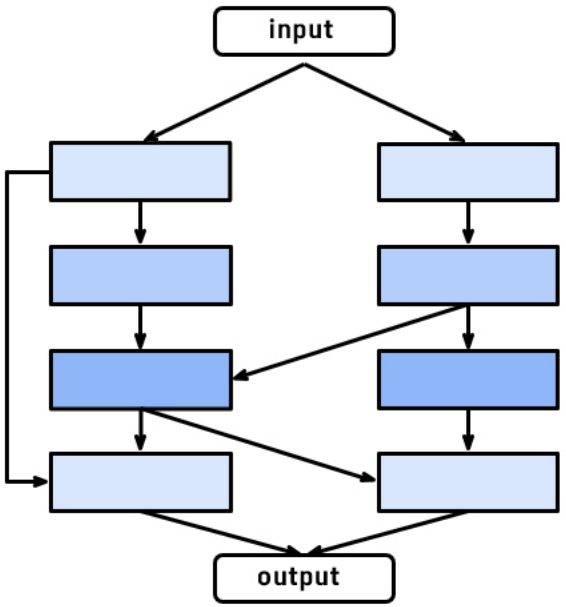
# Macro Architecture Search Space

**Contains individual layers and connection types**

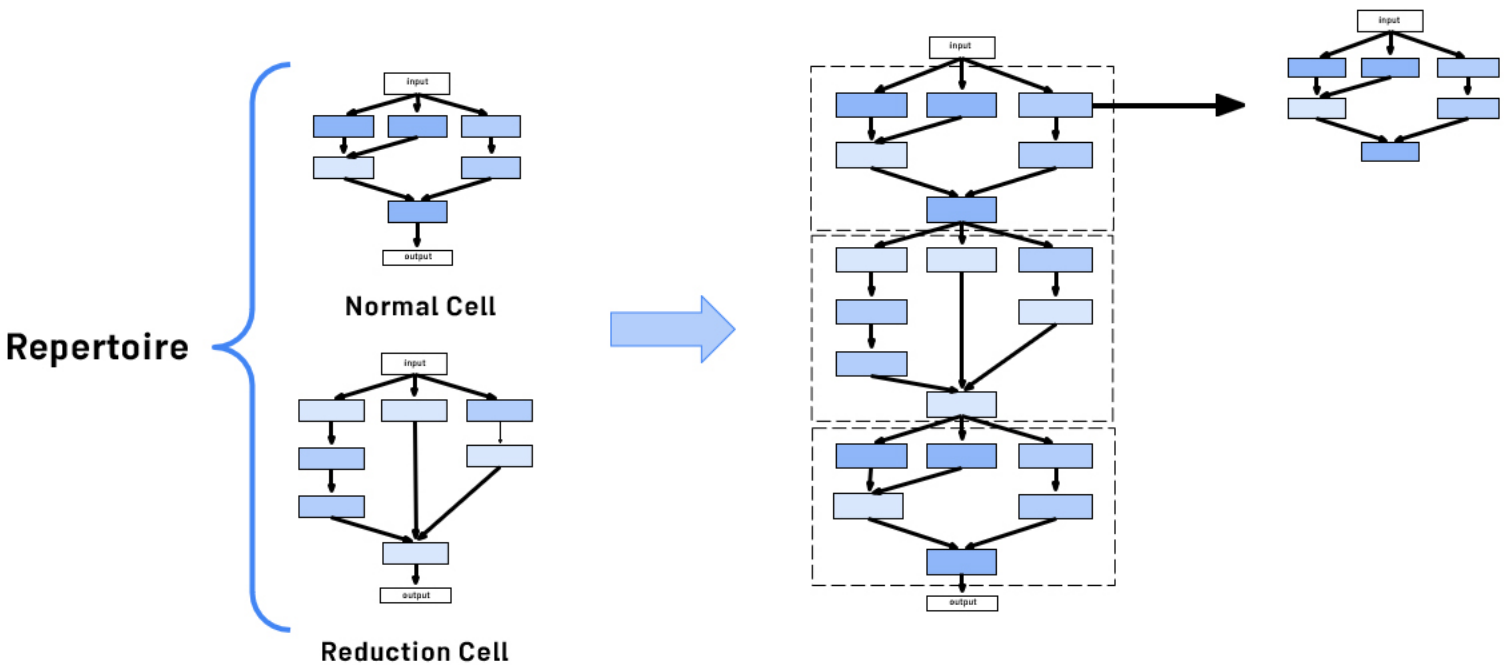
Chain structured space




Complex search space

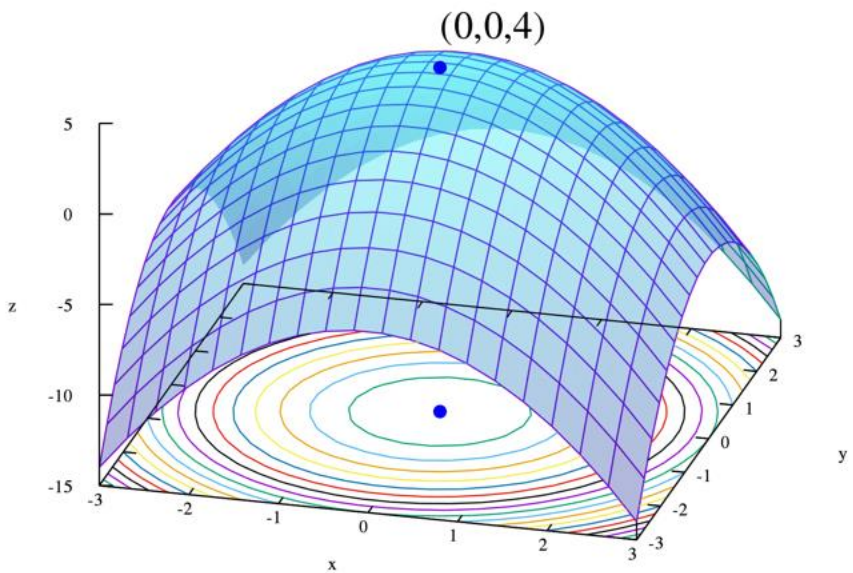


# Micro Architecture Search Space



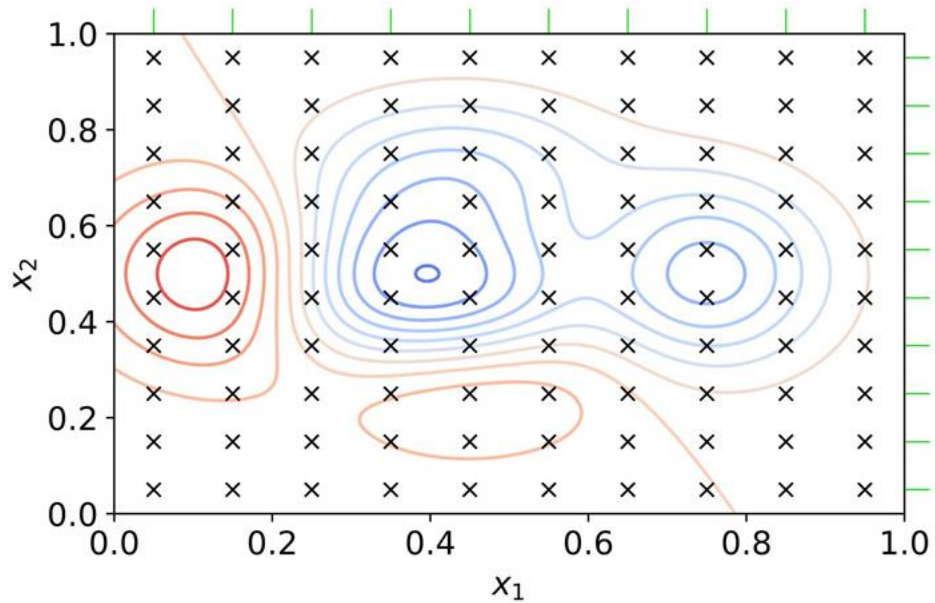
# A Few Search Strategies

- Grid Search
- Random Search
- Bayesian Optimization
- Evolutionary Algorithms
- Reinforcement Learning



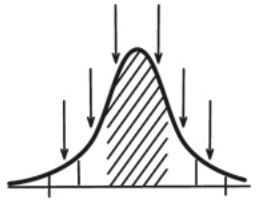
# Grid Search and Random Search

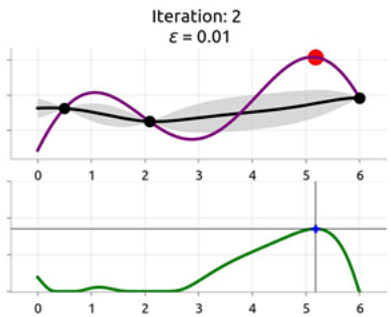
- **Grid Search**
  - Exhaustive search approach on fixed grid values
- **Random Search**
- **Both suited for smaller search spaces.**
- **Both quickly fail with growing size of search space.**



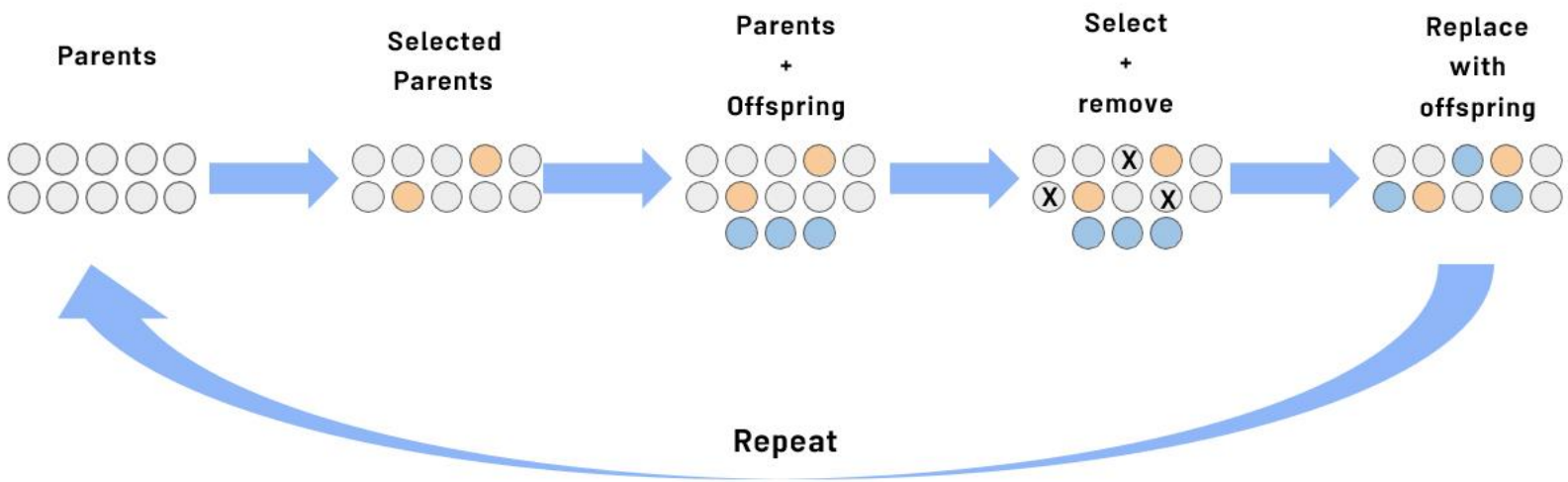
# Bayesian Optimization

- 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.



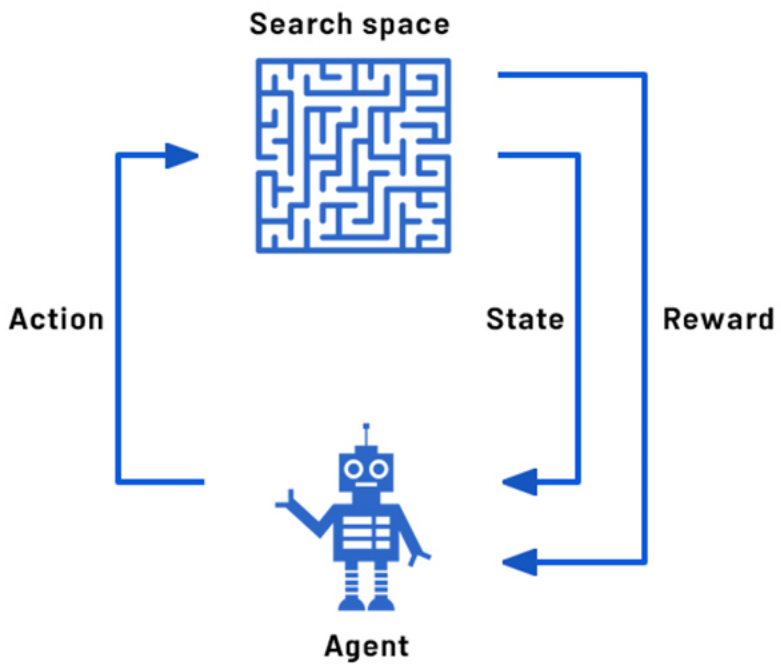


# Evolutionary Methods

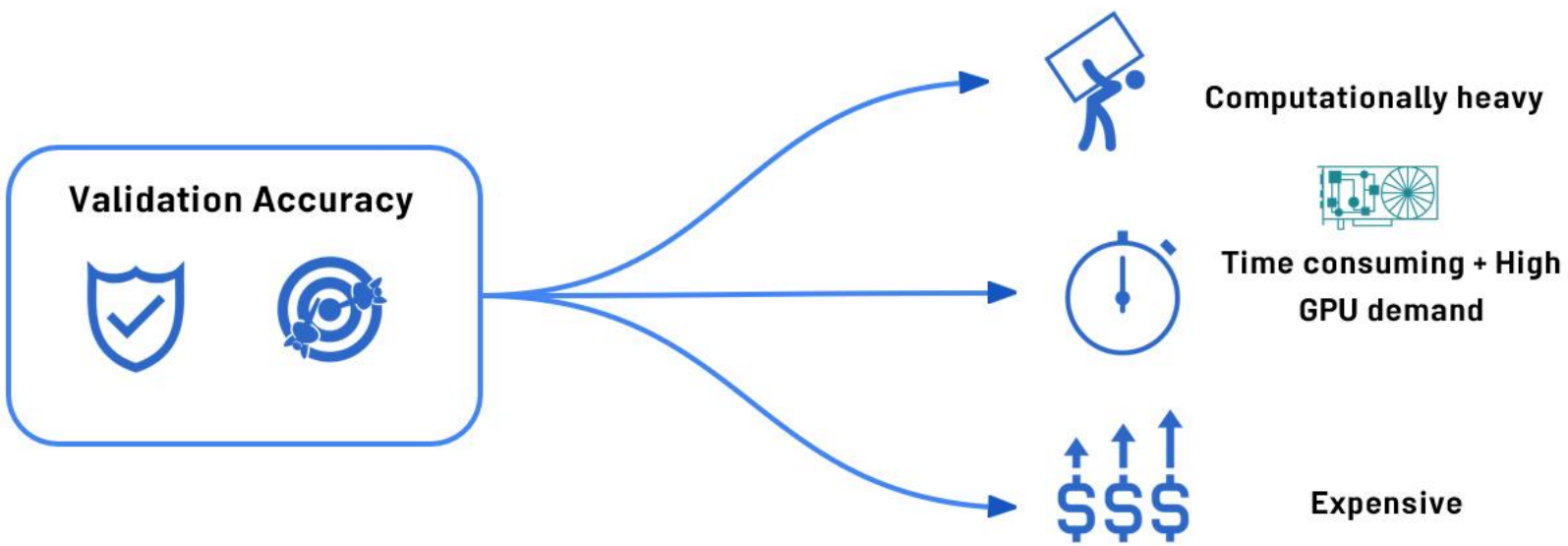


# Reinforcement Learning

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



# Performance Estimation Strategy

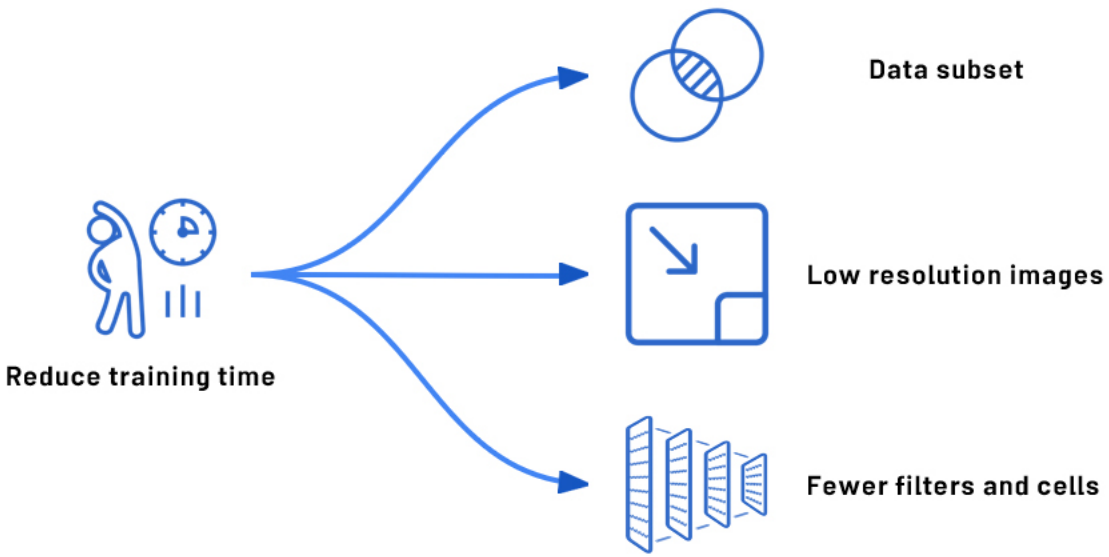


# Strategies to Reduce the Cost

- Lower fidelity estimates
- Learning Curve Extrapolation
- Weight Inheritance/ Network Morphisms

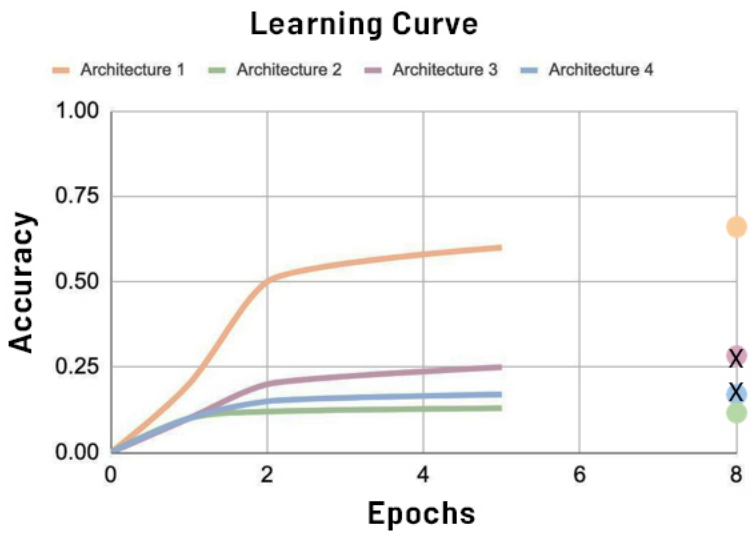
# Lower Fidelity Estimates

- 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

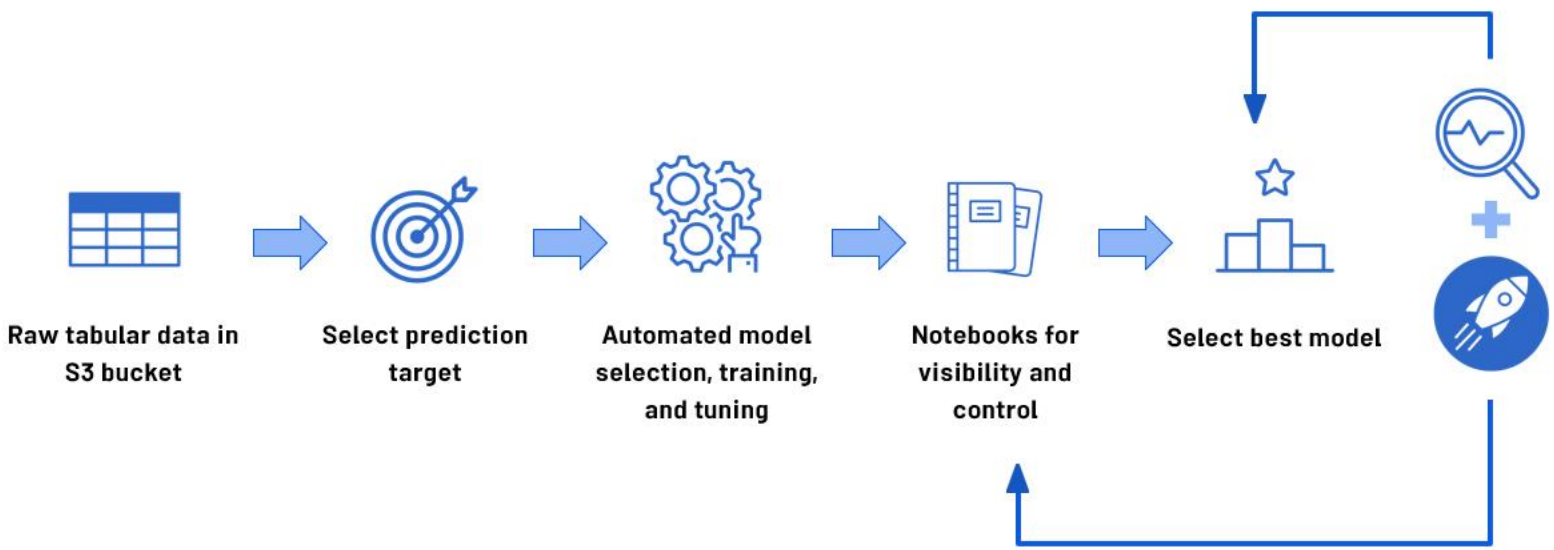
- Initialize weights of new architectures based on previously trained architectures
  - Similar to transfer learning
- Uses Network Morphism
- Underlying function unchanged
  - New network inherits knowledge from parent network.
  - Computational speed up: only a few days of GPU usage
  - Network size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

# Popular Cloud Offerings

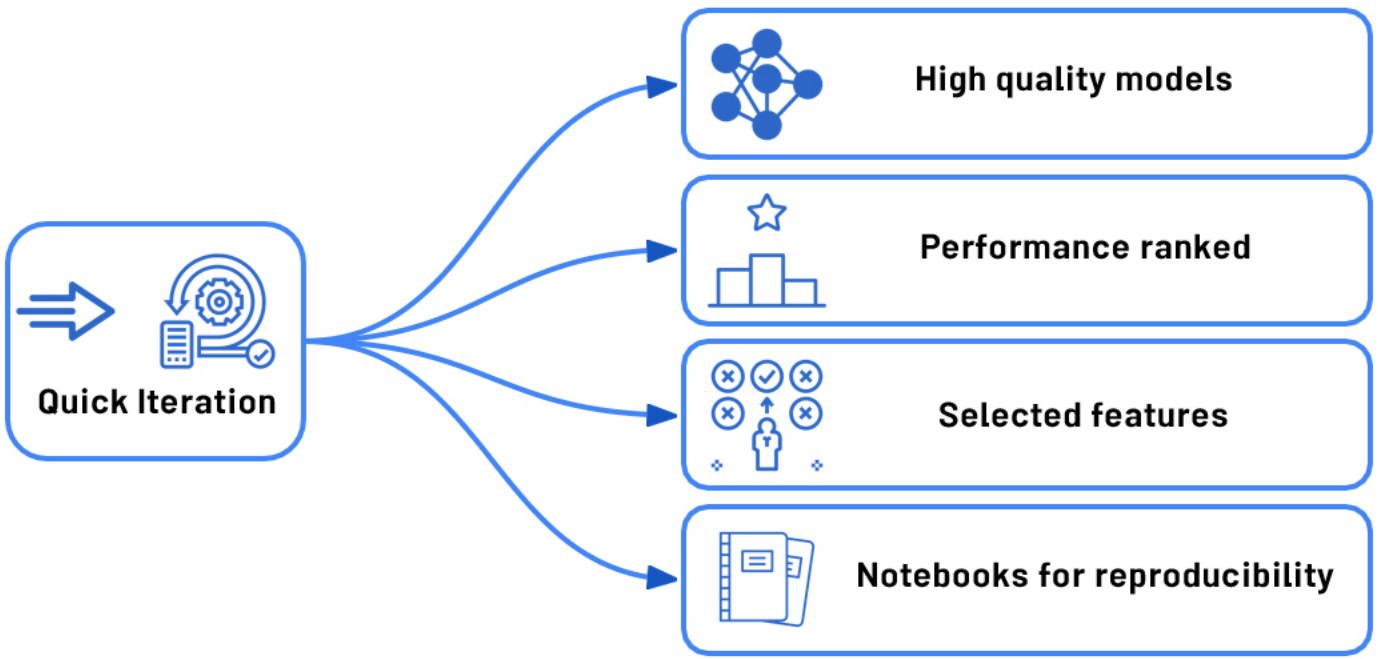
Cloud-based AutoML

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

# Amazon SageMaker Autopilot



# Key features



# 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