

# Hierarchical Representations for Efficient Architecture Search

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STAT946 Deep Learning

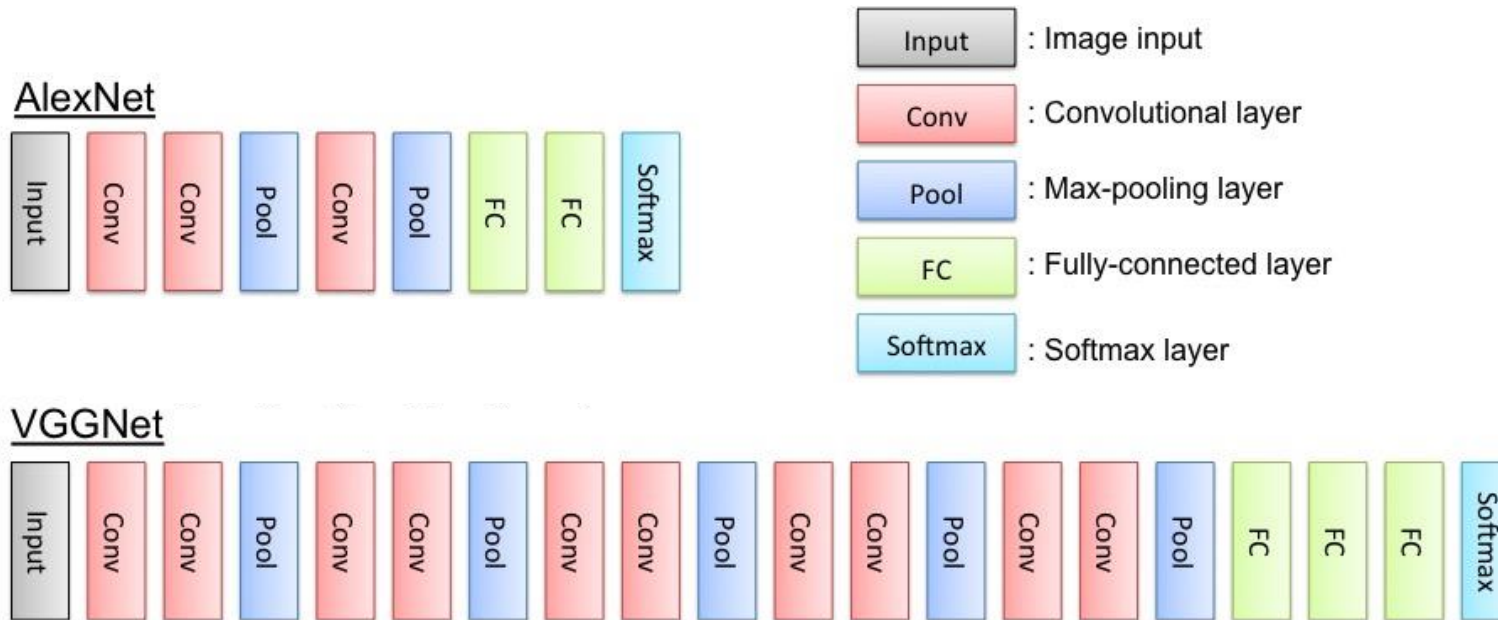


# Outline

- Introduction
- Architecture representations
- Evolutionary architecture search
- Experiments and results
- Contributions and critique

# Introduction

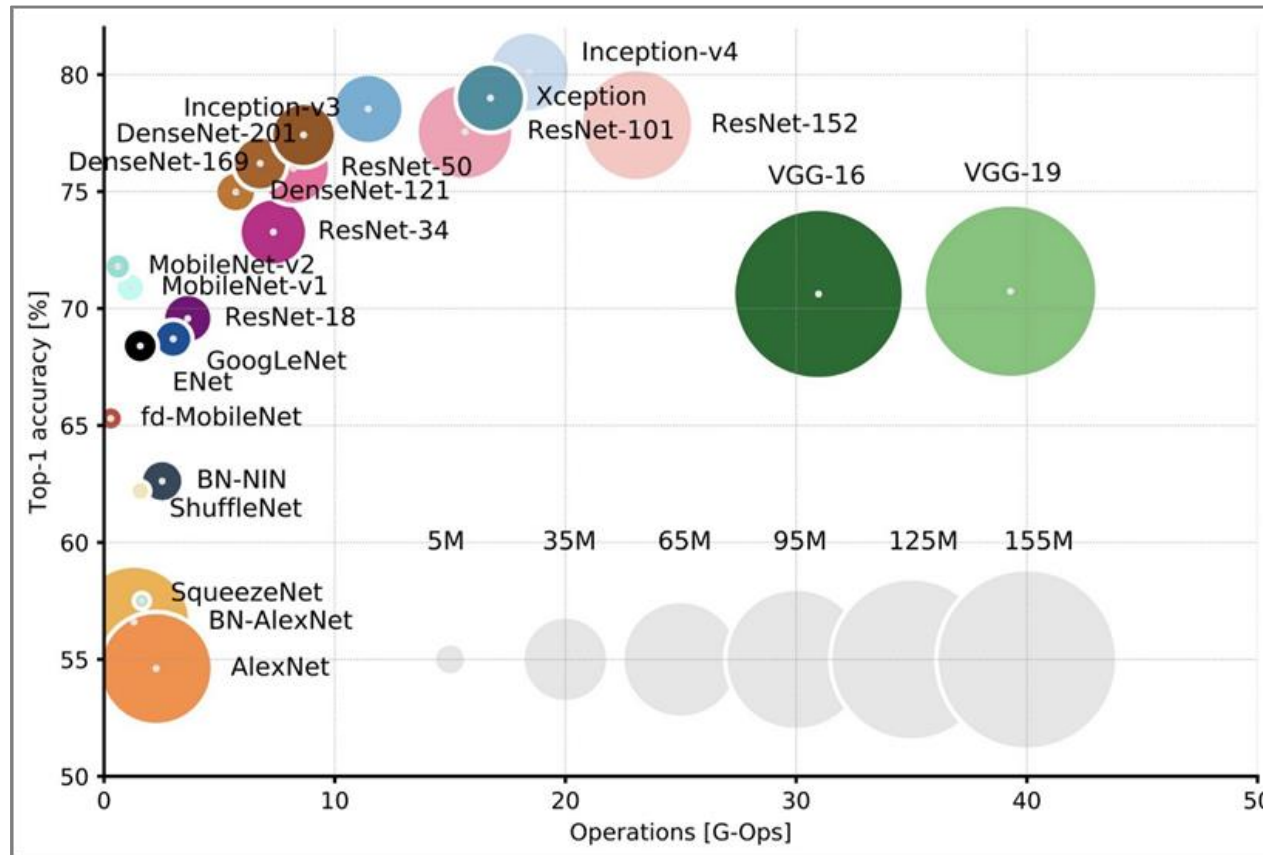
## Deep Neural Network Architectures for Image Classification



Source: <http://www.hirokatsukataoka.net/research/cnnfeatureevaluation/cnnfeatureevaluation.html>

# Introduction

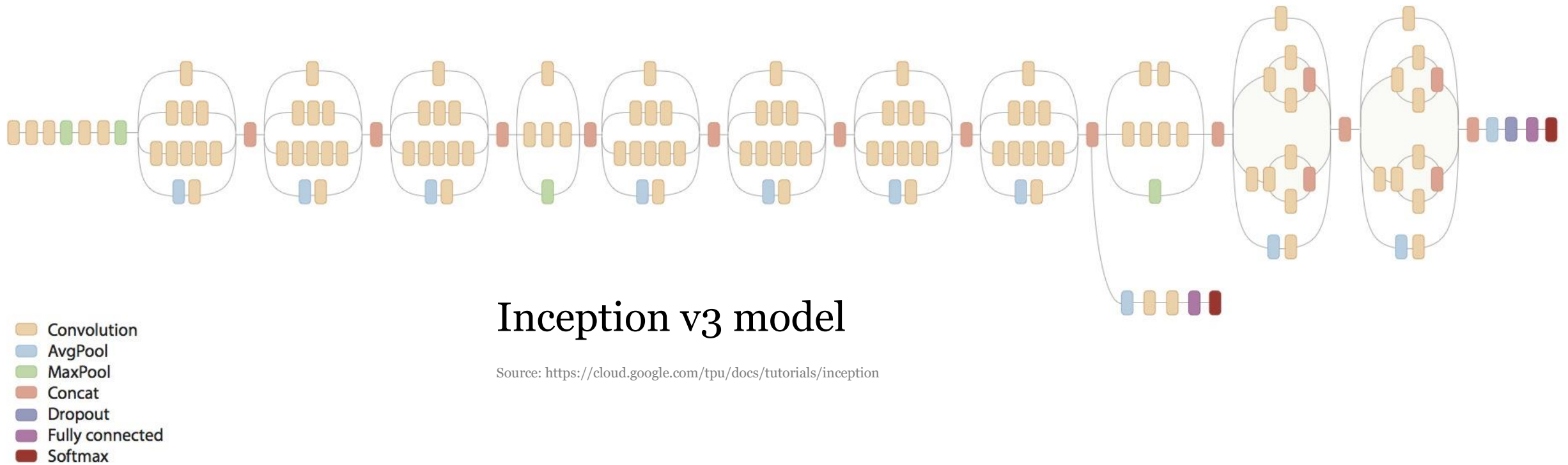
## Computation cost versus accuracy



Source: <https://arxiv.org/abs/1605.07678>

# Introduction

## Increasing complexity of Deep Neural Networks



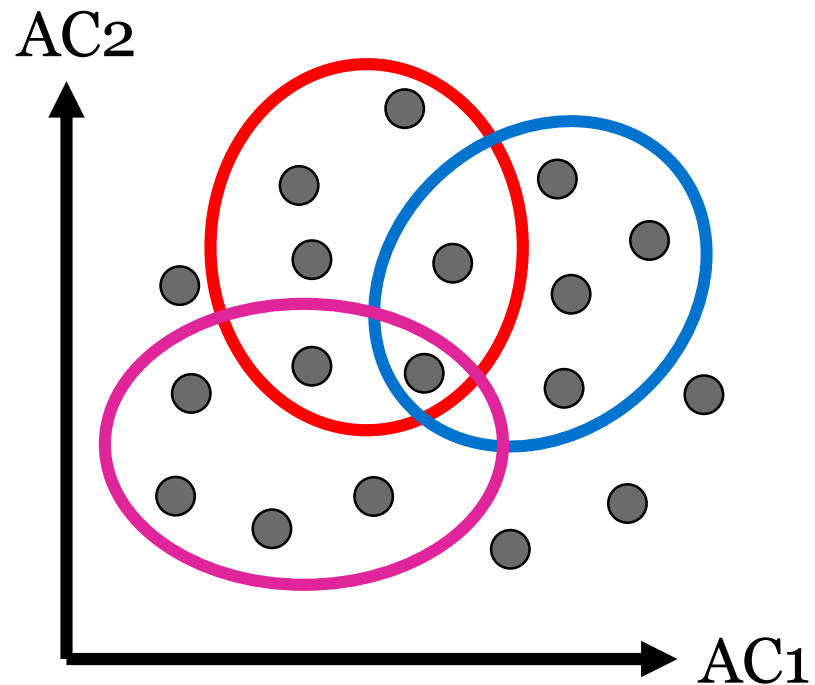
### Inception v3 model

Source: <https://cloud.google.com/tpu/docs/tutorials/inception>

# Introduction

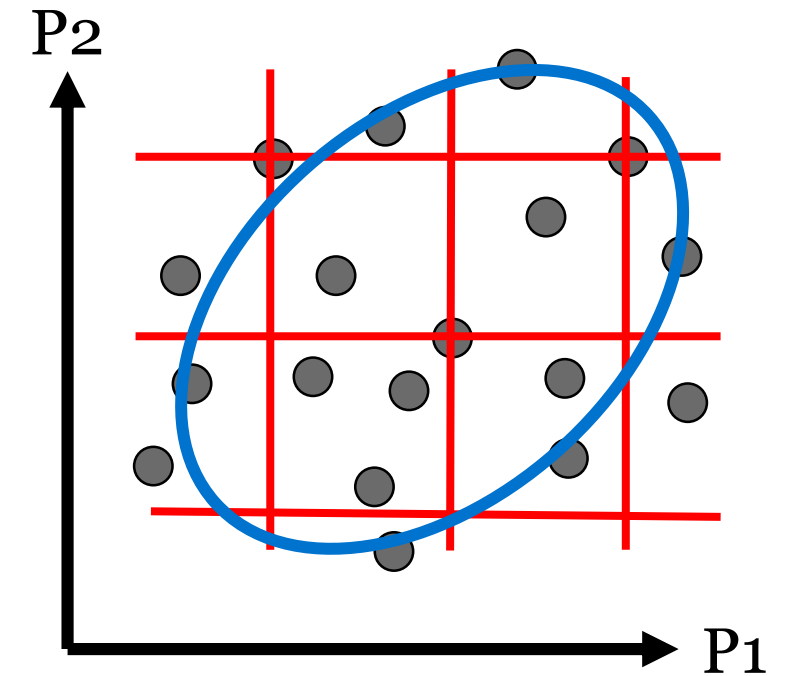
## Architecture search

- MCTS
- RL
- Evolut.



## Parameter search a.k.a. “Hyperparameter tuning”

- Grid
- Rand.



# Architecture representations

## Primitive operations

$O^{(level)}$   
*operation id*

$o_1^{(1)}$  *1 x 1 convolution of C channels*

$o_2^{(1)}$  *3 x 3 depth wise convolution*

$o_3^{(1)}$  *3 x 3 separable convolution of C channels*

$o_4^{(1)}$  *3 x 3 max pooling*

$o_5^{(1)}$  *3 x 3 average pooling*

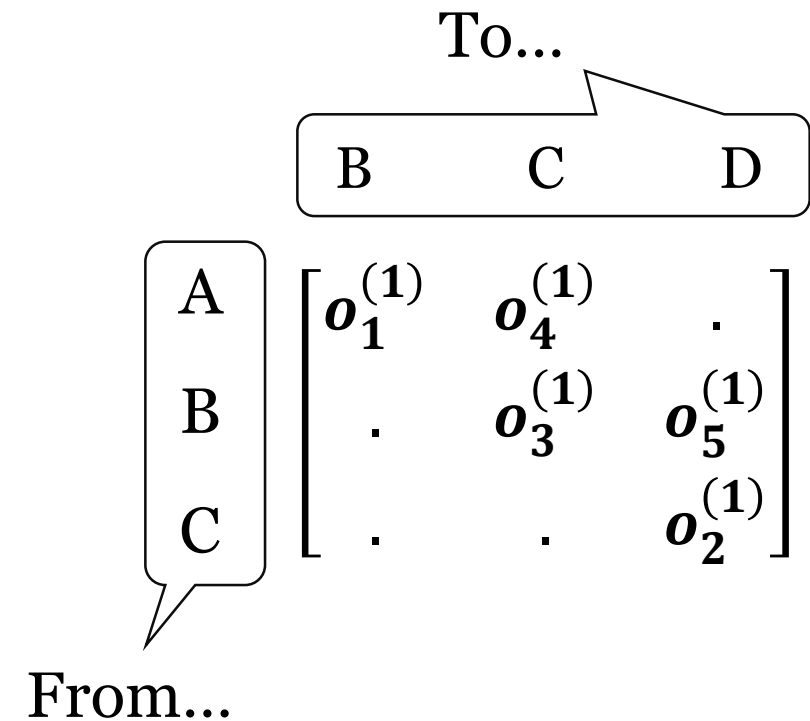
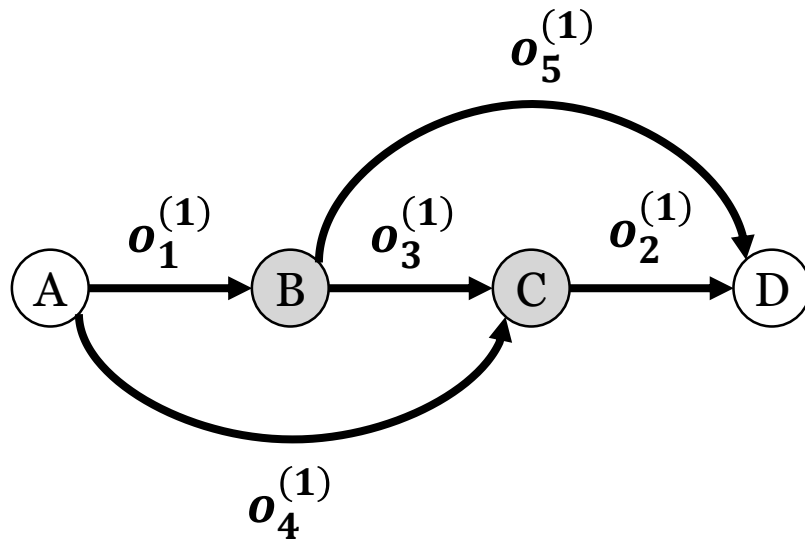
$o_6^{(1)}$  *identity*

Convolutional operations are followed by batch normalization and ReLU activation

# Architecture representations

## Flat representation

- Nodes are feature maps (a.k.a. vectors or matrices)
- Edges are primitive operations

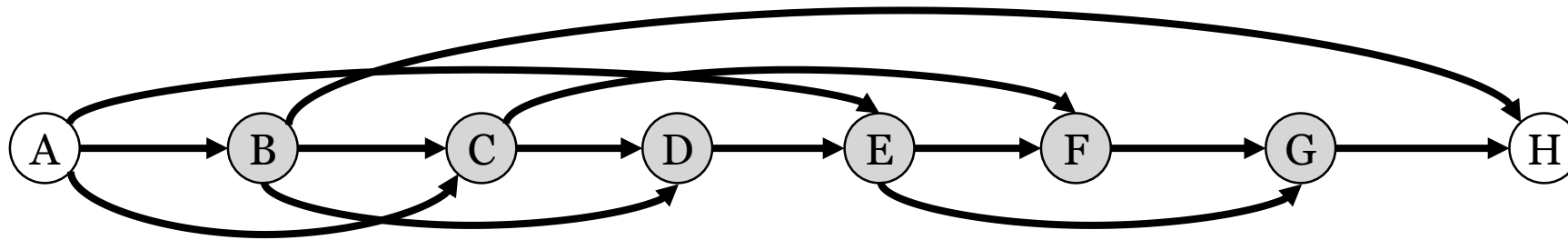




# Architecture representations

## Flat representation

- Flat networks can grow to very complex models.

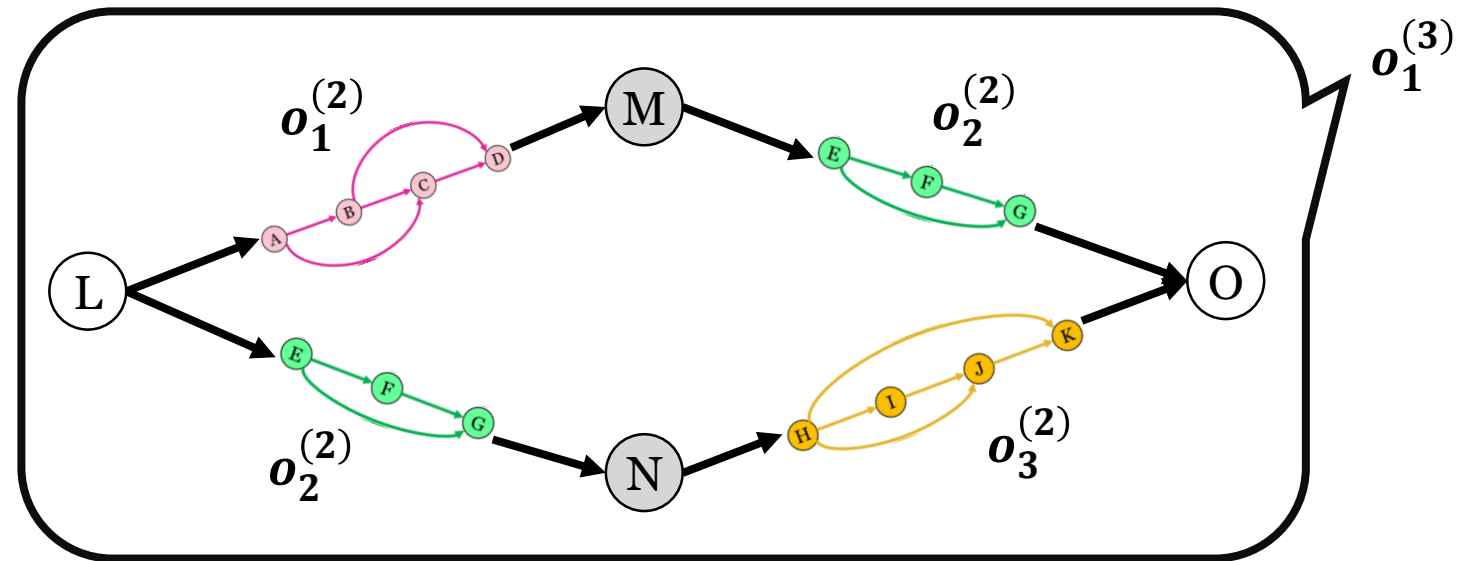
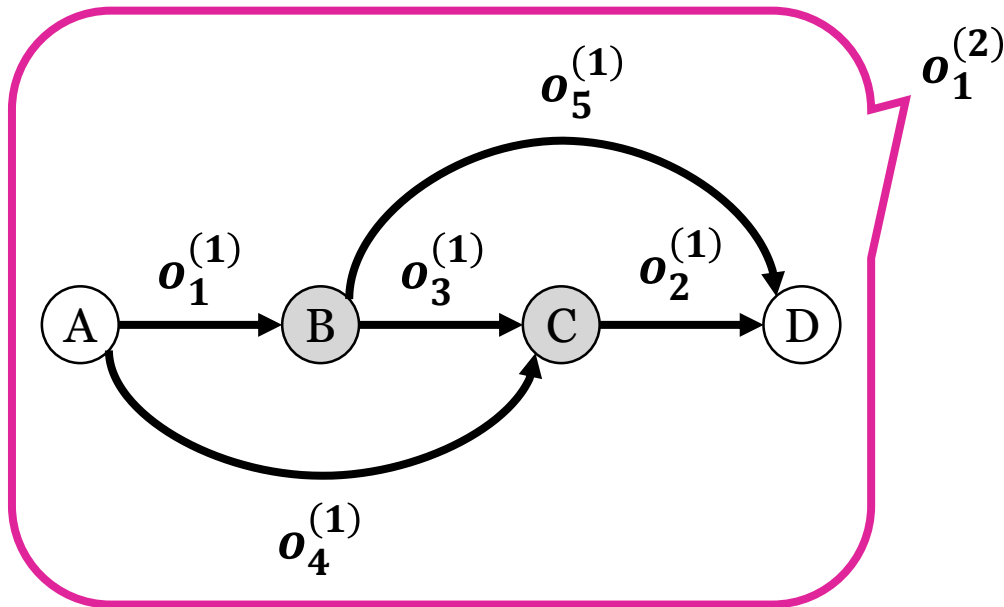


# Architecture representations

## Hierarchical representation

- Nodes are feature maps (a.k.a. vectors or matrices)
- Edges are higher level operations (a.k.a. motifs)

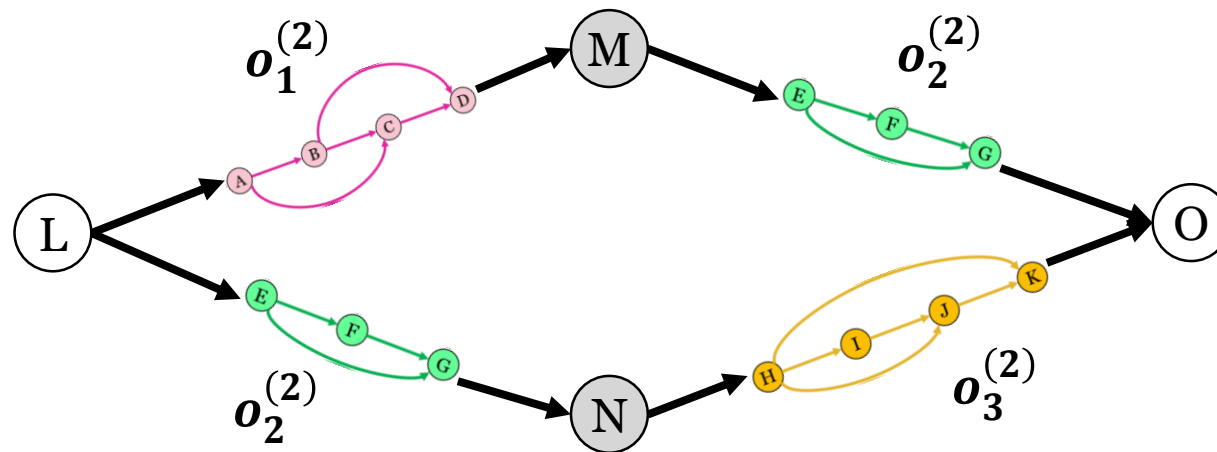
$$\begin{array}{c}
 \begin{array}{ccc}
 & M & N & O \\
 L & \begin{bmatrix} \mathbf{o}_1^{(2)} & \mathbf{o}_2^{(2)} & \cdot \\ \cdot & \cdot & \mathbf{o}_2^{(2)} \\ \cdot & \cdot & \mathbf{o}_3^{(2)} \end{bmatrix} \\
 M & & & \\
 N & & & 
 \end{array}
 \end{array}$$



# Evolutionary architecture search

## Mutation

- Any NN architecture is treated as a genotype in a population.



Sample a non-primitive level



Sample a motif



Sample two nodes

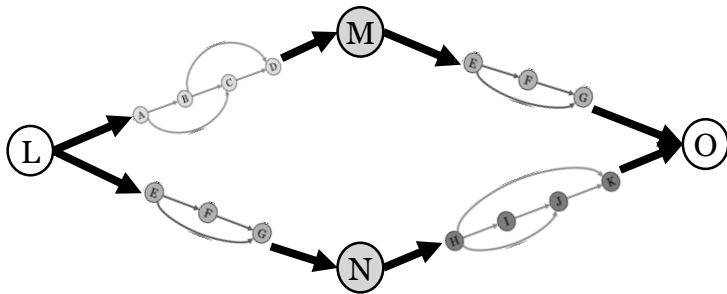


Change current operation

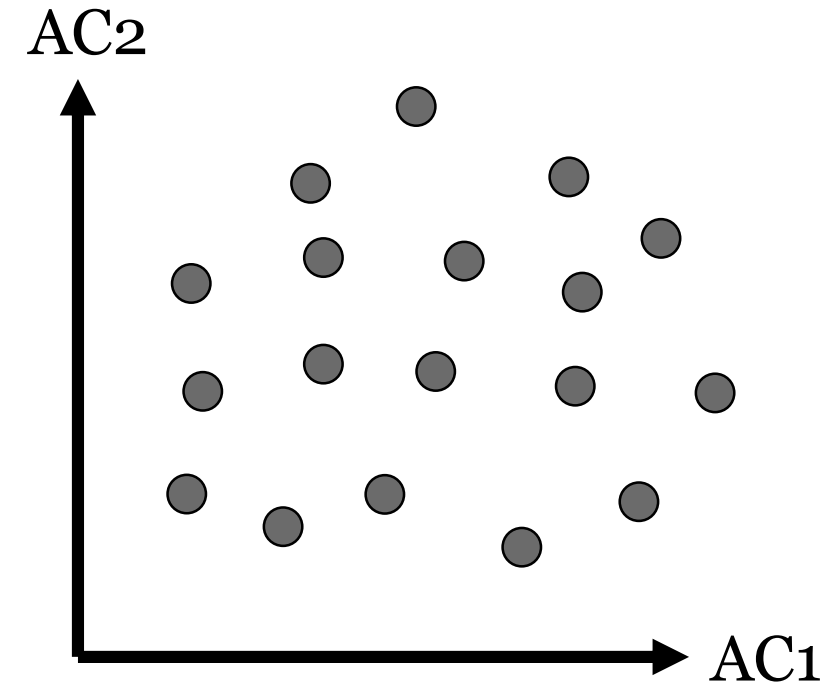
# Evolutionary architecture search

## Initialization

Trivial genotype where all operations are identity



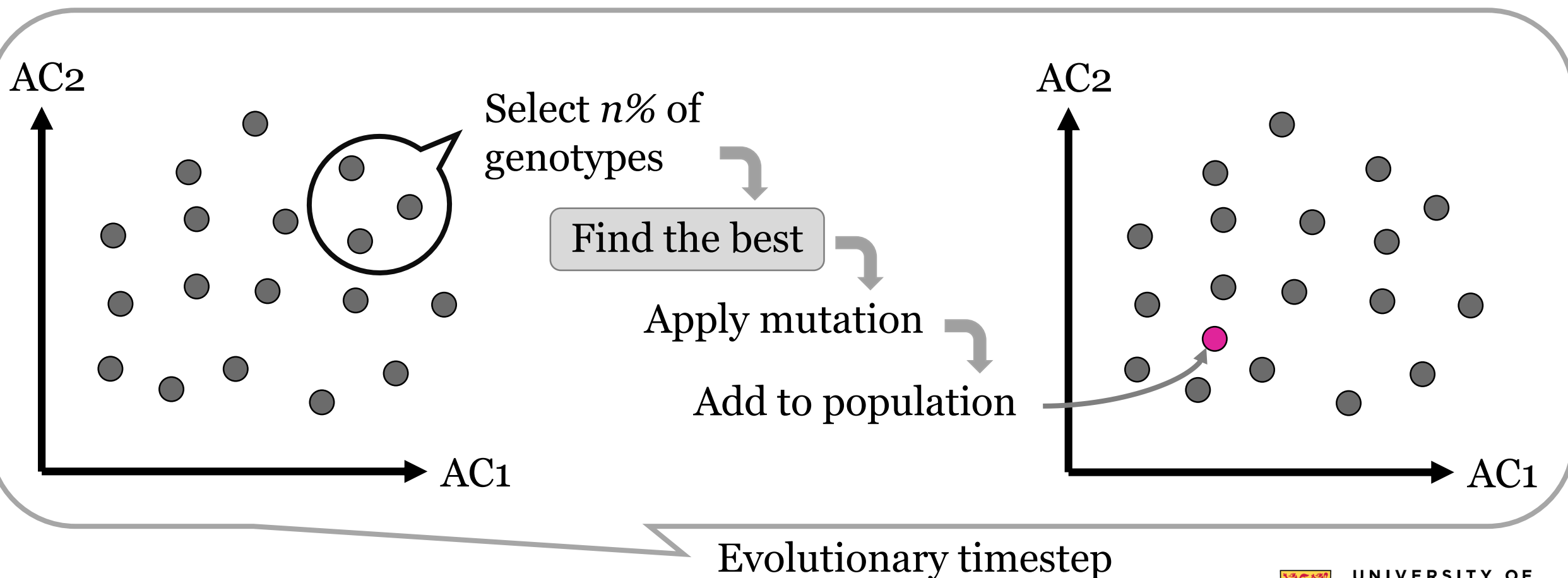
Mutation



Initialization timestep

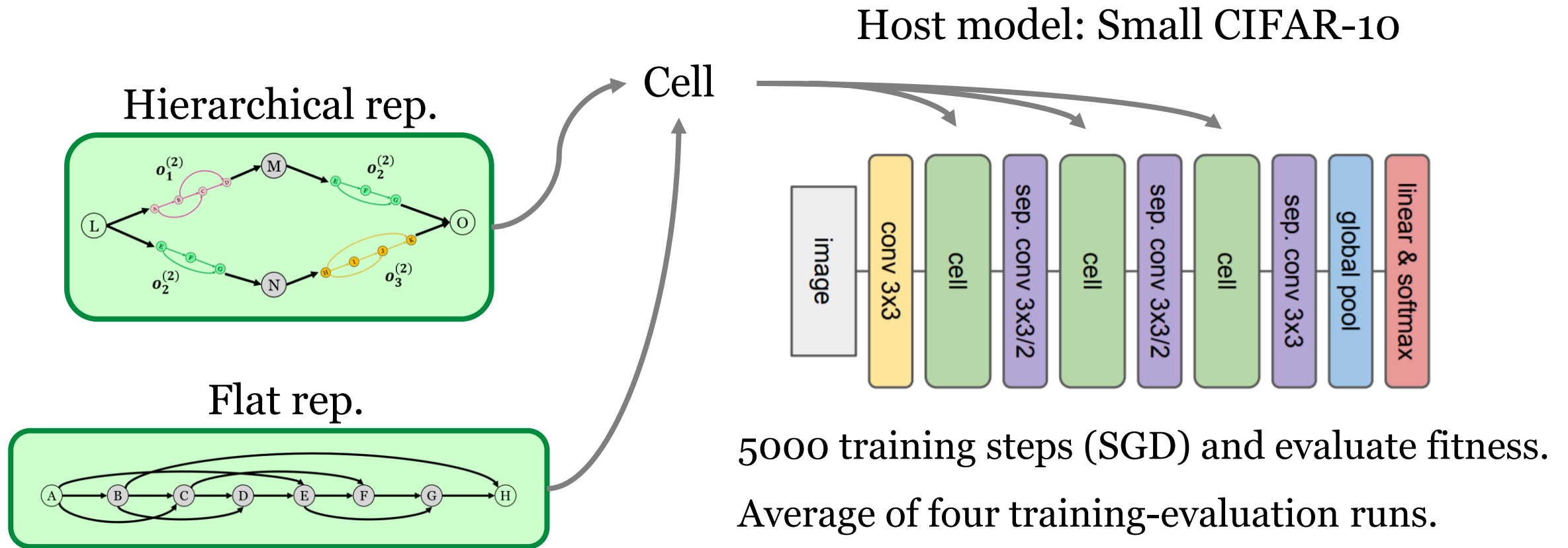
# Evolutionary architecture search

## Search algorithm: Tournament selection



# Experiments and results

## Architecture search on small CIFAR-10

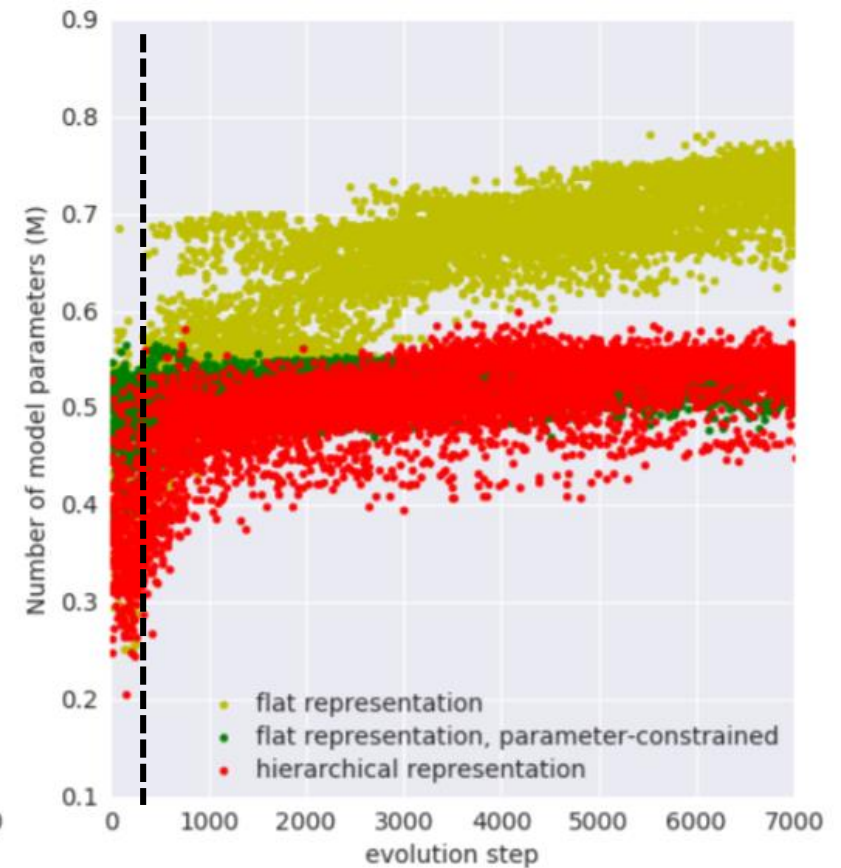
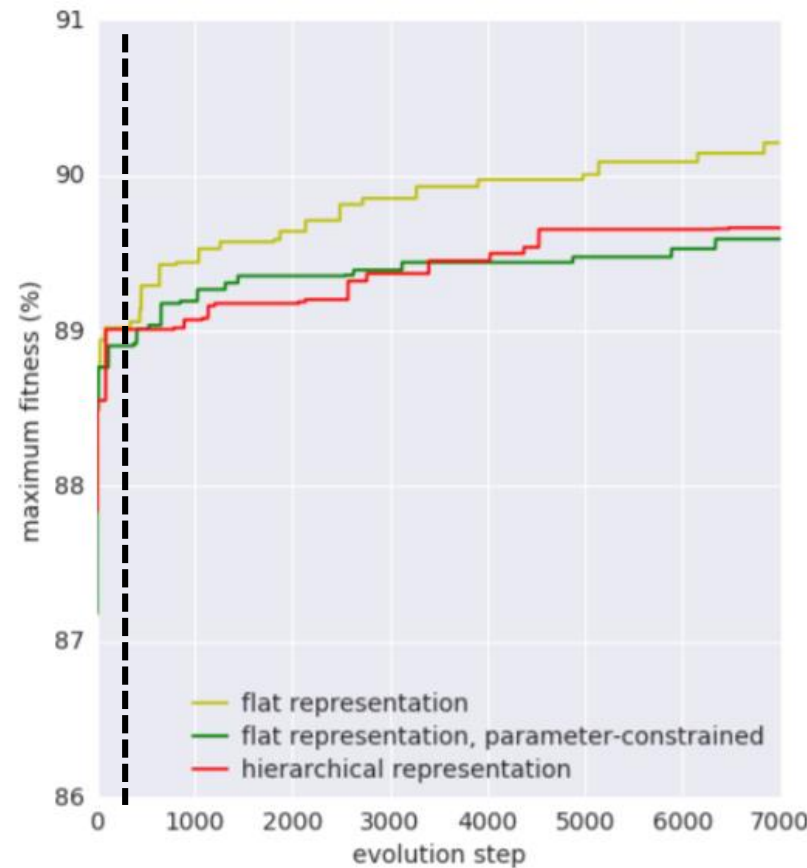
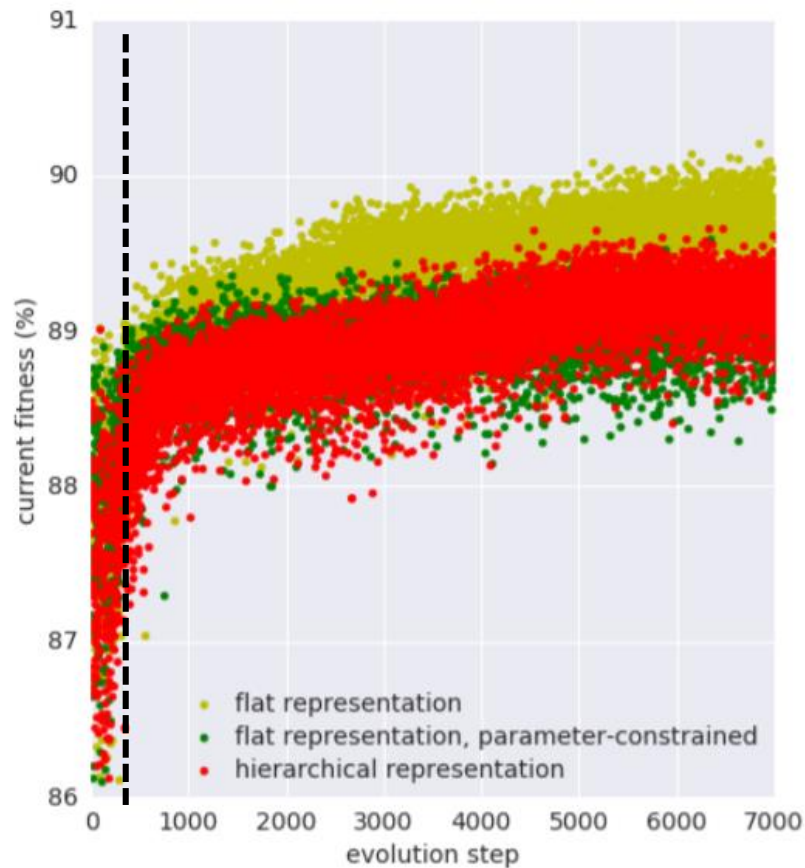


# Experiments and results

Step 1 to step 200: Initialization

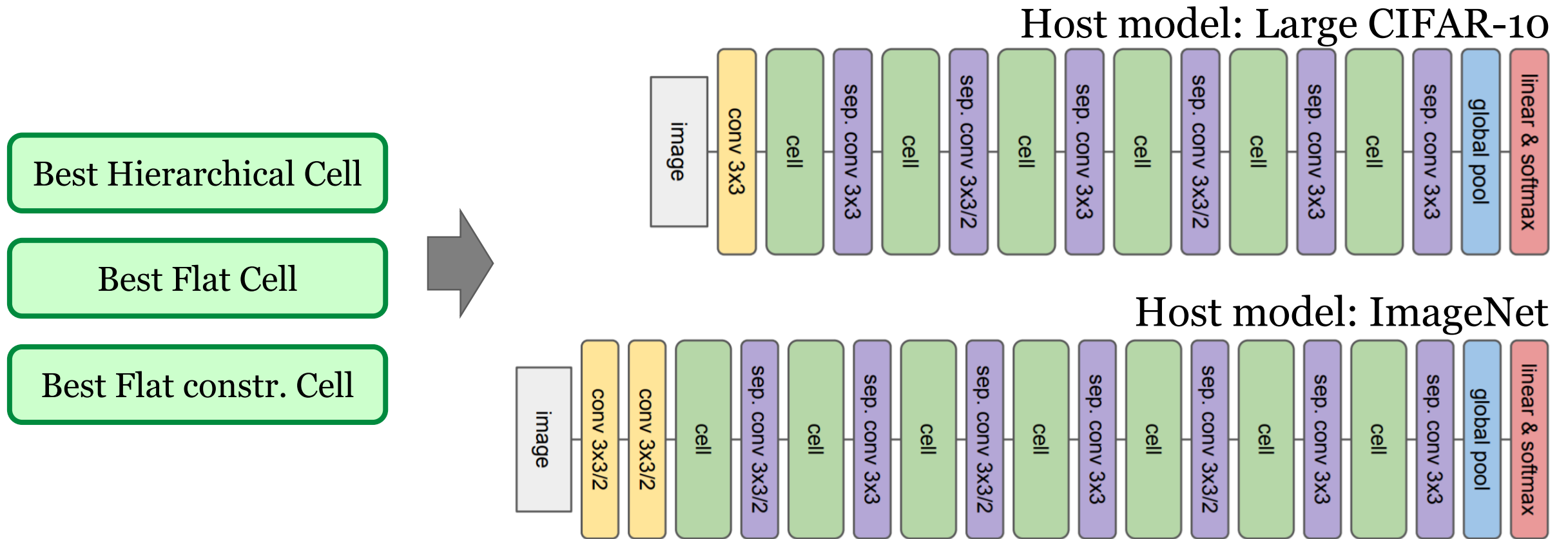
Step 201 to step 7000: Evolution

## Architecture search on small CIFAR-10



# Experiments and results

## Architecture evaluation on large CIFAR-10 and ImageNet





# Experiments and results

## Architecture evaluation on large CIFAR-10 and ImageNet

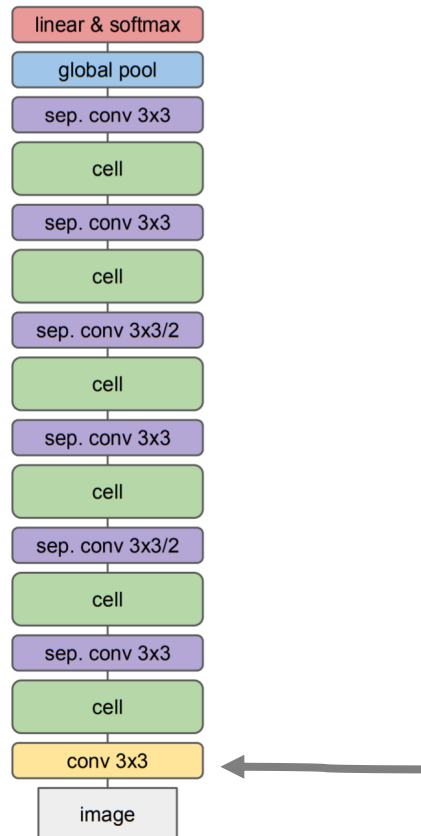
Search Method	CIFAR-10 error (%)	ImageNet Top-1/Top-5 error (%)
Flat repr-n, random architecture	$4.56 \pm 0.11$	21.4/5.8
Flat repr-n, random search (200 samples)	$4.02 \pm 0.11$	20.8/5.7
→ Flat repr-n, evolution (7000 samples)	$3.92 \pm 0.06$	20.6/5.6
Flat repr-n, parameter-constrained, evolution (7000 samples)	$4.17 \pm 0.08$	21.2/5.8
Hier. repr-n, random architecture	$4.21 \pm 0.11$	21.5/5.8
Hier. repr-n, random search (200 samples)	$4.04 \pm 0.2$	20.4/5.3
Hier. repr-n, random search (7000 samples)	$3.91 \pm 0.15$	21.0/5.5
→ Hier. repr-n, evolution (7000 samples) ★	<b><math>3.75 \pm 0.12</math></b>	<b>20.3/5.2</b>

The best type of cells is?



# Experiments and results

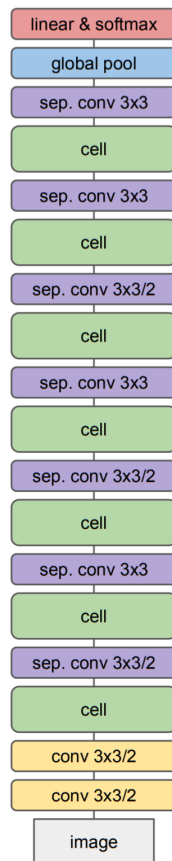
## Comparison against other models on CIFAR-10



Model	Error (%)
ResNet-1001 + pre-activation (He et al., 2016b)	4.62
Wide ResNet-40-10 + dropout (Zagoruyko & Komodakis, 2016)	3.8
DenseNet (k=24) (Huang et al., 2016)	3.74
DenseNet-BC (k=40) (Huang et al., 2016)	3.46
MetaQNN (Baker et al., 2016)	6.92
NAS v3 (Zoph & Le, 2016)	3.65
Block-QNN-A (Zhong et al., 2017)	3.60
NASNet-A (Zoph et al., 2017)	3.41
Evolving DNN (Miikkulainen et al., 2017)	7.3
Genetic CNN (Xie & Yuille, 2017)	7.10
Large-scale Evolution (Real et al., 2017)	5.4
SMASH (Brock et al., 2017)	4.03
Evolutionary search, hier. repr., $c_0 = 64$	$3.75 \pm 0.12$
Evolutionary search, hier. repr., $c_0 = 128$	$3.63 \pm 0.10$

# Experiments and results

## Comparison against other models on ImageNet



Model	Top-1 error (%)	Top-5 error (%)
Inception-v3 (Szegedy et al., 2016)	21.2	5.6
Xception (Chollet, 2016)	21.0	5.5
Inception-ResNet-v2 (Szegedy et al., 2017)	19.9	4.9
NASNet-A (Zoph et al., 2017)	19.2	4.7
Evolutionary search, hier. repr., $c_0 = 64$	20.3	5.2

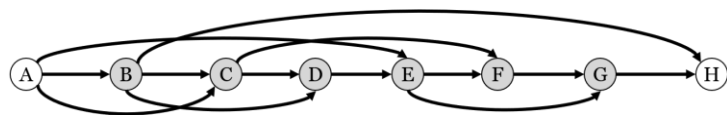
# Contributions

A new evolutionary framework is introduced for searching neural network architectures over searching spaces defined by flat and hierarchical representations of a convolutional cell.

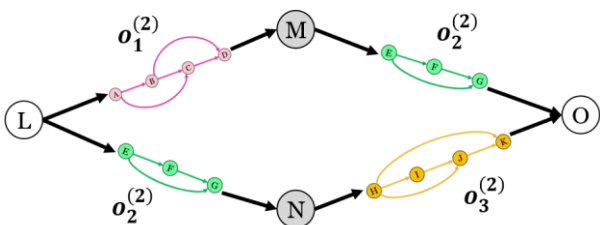
Experiments show that the proposed framework achieves competitive results against state-of-the-art classifiers on the CIFAR-10 and ImageNet datasets.

# Critique

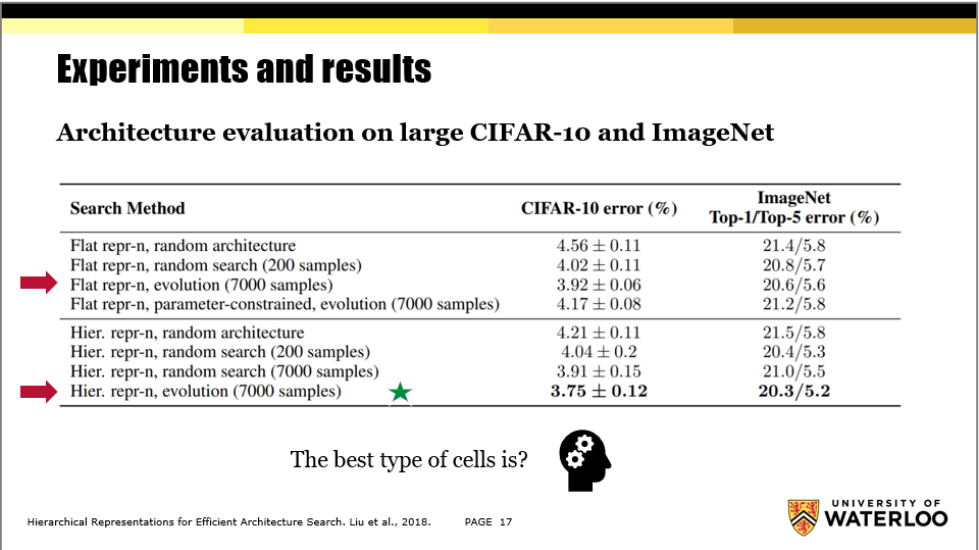
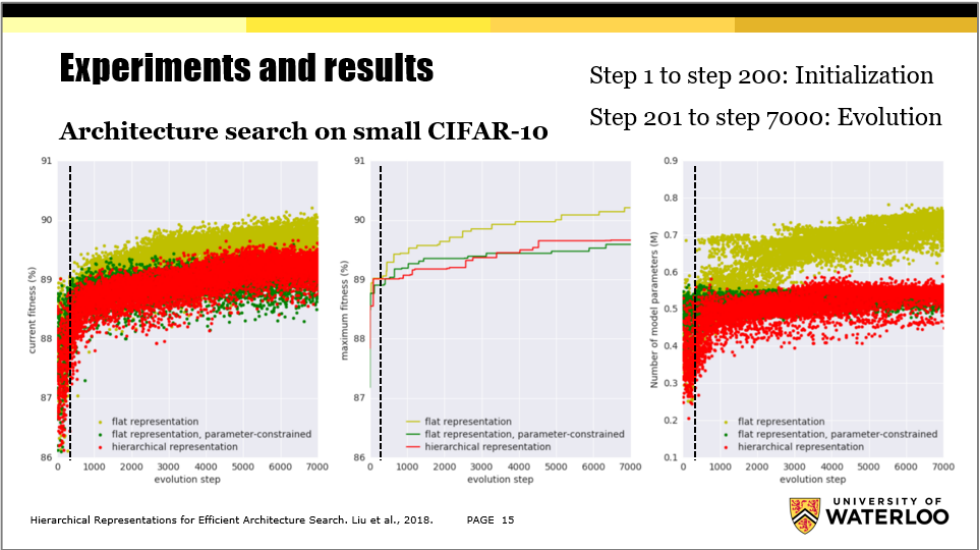
What is the best type of cell?



Flat representation



Hierarchical representation



# Questions?



Source: <https://www.theacademygtc.co.uk/thinking-man-wasnt-a-thing/>