



Neural Architecture Search in Graph Neural Networks

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Motivation

- ◎ Graphs are ubiquitous (e.g. chemistry, social networks, movies, etc.)
- ◎ Graph Neural Networks (GNNs) are state-of-the-art techniques for ML in Graphs but their design is currently hand-made and error-prone

Motivation

- ◎ AutoML techniques such as Neural Architecture Search (NAS) have been successfully applied to CNNs for image data (e.g. CIFAR-10, ImageNet)
- ◎ However, there are very few works that explore NAS for GNNs
 - Auto-GNN (Zhou et. al., 2019)
 - GraphNAS (Gao et. al., 2020)

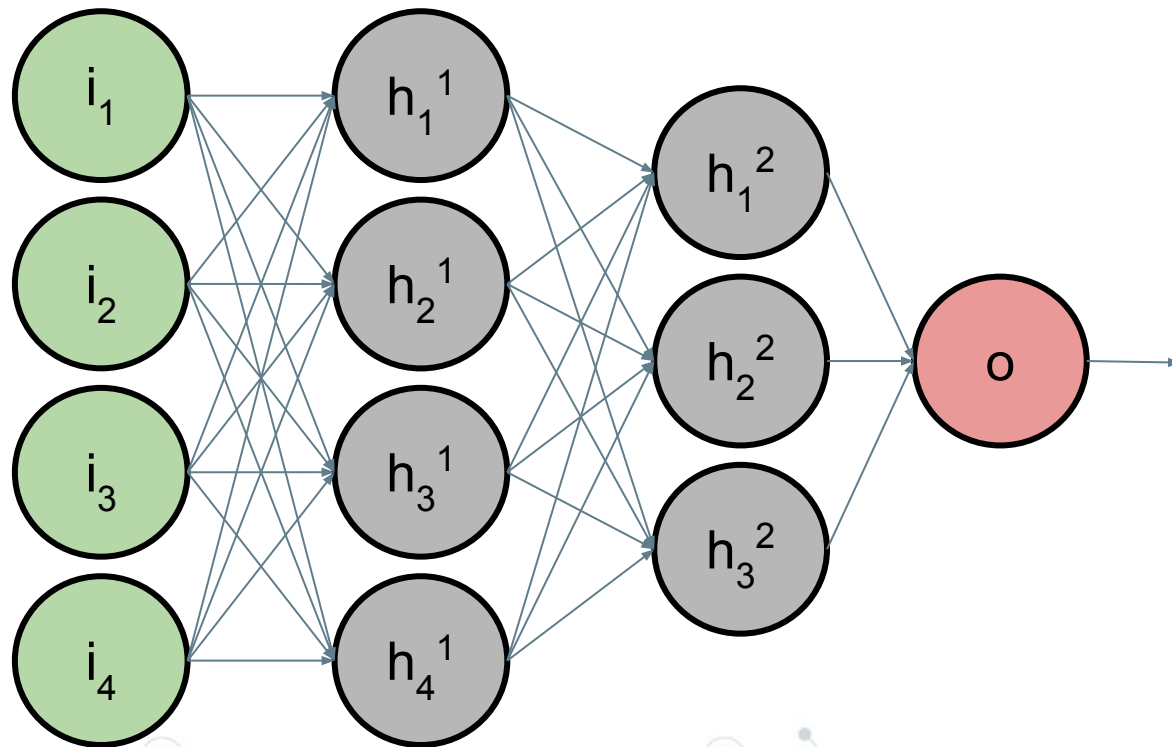
Motivation

- ◎ Both Auto-GNN and GraphNAS use Reinforcement Learning (RL) as an optimization technique
 - Evolutionary Algorithms (EAs) have been shown to be competitive for CNNs
- ◎ Auto-GNN applies weight sharing to child arch. as speed up

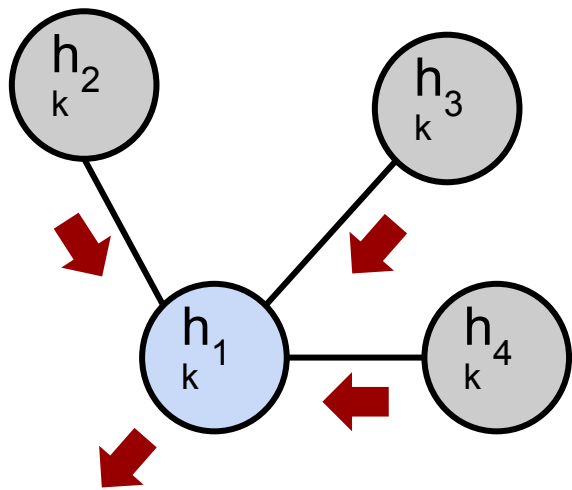
In this work

- ◎ Adapt and employ an EA previously proposed for image data on GraphNAS' search space
 - Regularized evolution (Real et. al., 2019)
- ◎ Compare with RL and Random Search (RS) in terms of the validation accuracy of the best architecture found and overall execution runtime

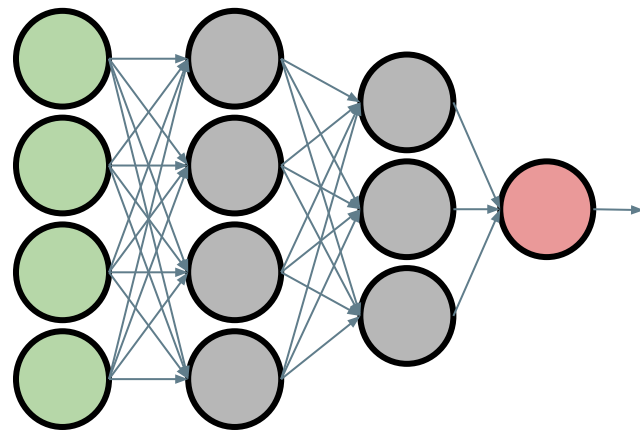
Background: GNNs



Background: GNNs



$$out = softmax(h_i)$$



$h_i^0 = \text{node features}$

$$h_1^{k+1} = act(cmb(agg(h_2^k, h_3^k, h_4^k), h_1^k))$$

Background: NAS

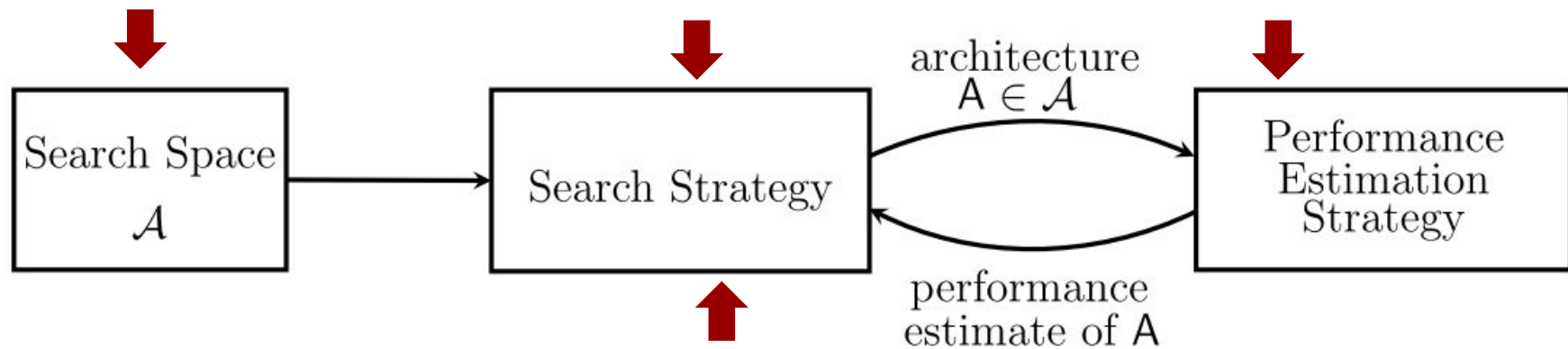


Image from: *Elsken et. al., Neural Architecture Search: A Survey. JMLR'19.*

In this work

- ◎ Evaluate the performance of 3 search methods (EA, RL, RS) over 2 search spaces from GraphNAS (Macro, Micro)
 - Spaces differ in structure and size
- ◎ Performance measure: **validation accuracy** after 300 training epochs in child arch.

Search Strategies

Reinforcement Learning (RL)

RNN controller generates child architectures

Policy gradient method with child arch. validation acc. as reward signal

Evolutionary Algorithm (EA)

Parent selected via tournament selection

Child arch. generated via mutation

Oldest individual removed from population

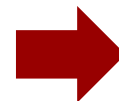
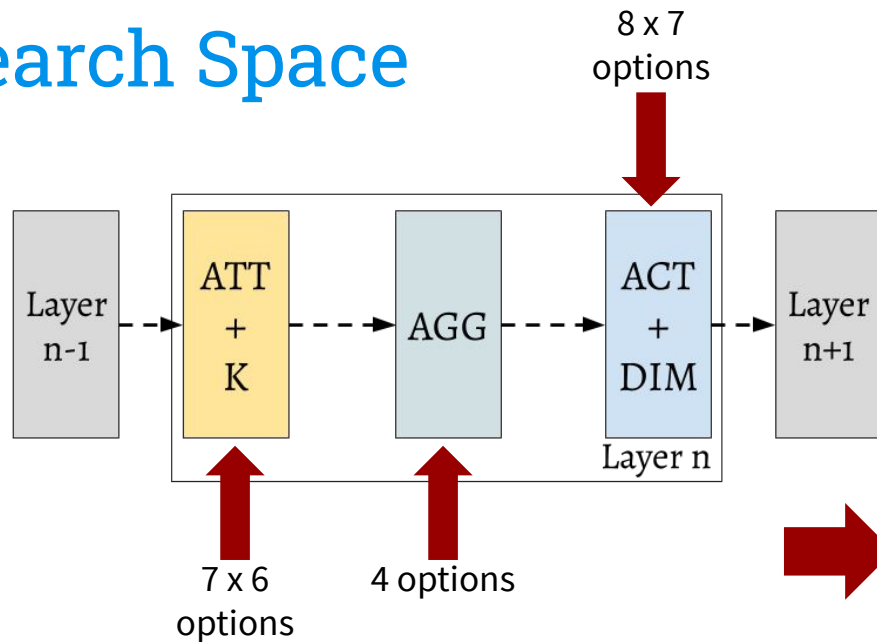
Random Search (RS)

Random architecture is generated

Trained and evaluated

Best architecture stored

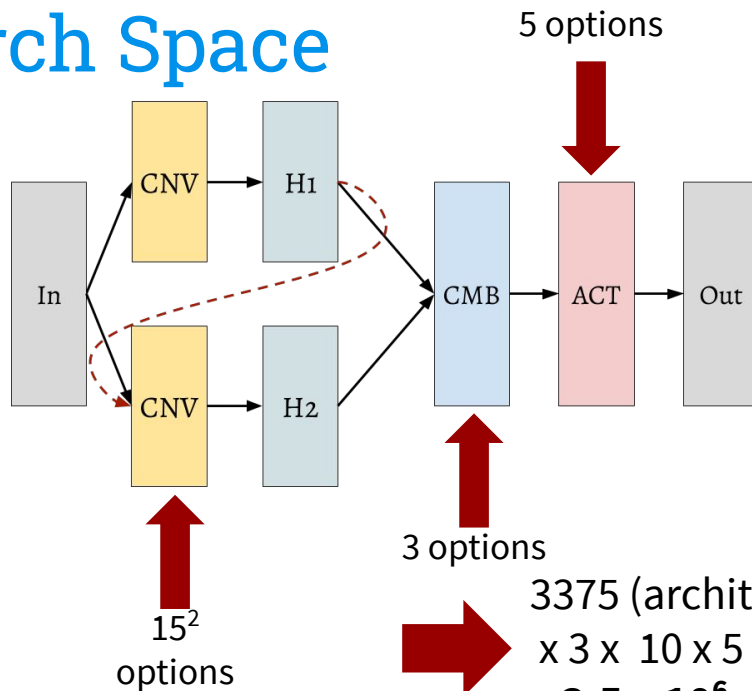
Macro Search Space



**9408 possibilities
in total!**

**Small space, always
uses graph attention,
no hyperparameter
tuning**

Micro Search Space



3375 (architectures)
x 3 x 10 x 5 x 7 options (hyperparameters)
= **3.5×10^6 possibilities in total.**
Larger space, multiple convolution operators, hyperparameter tuning

Experimental Analysis

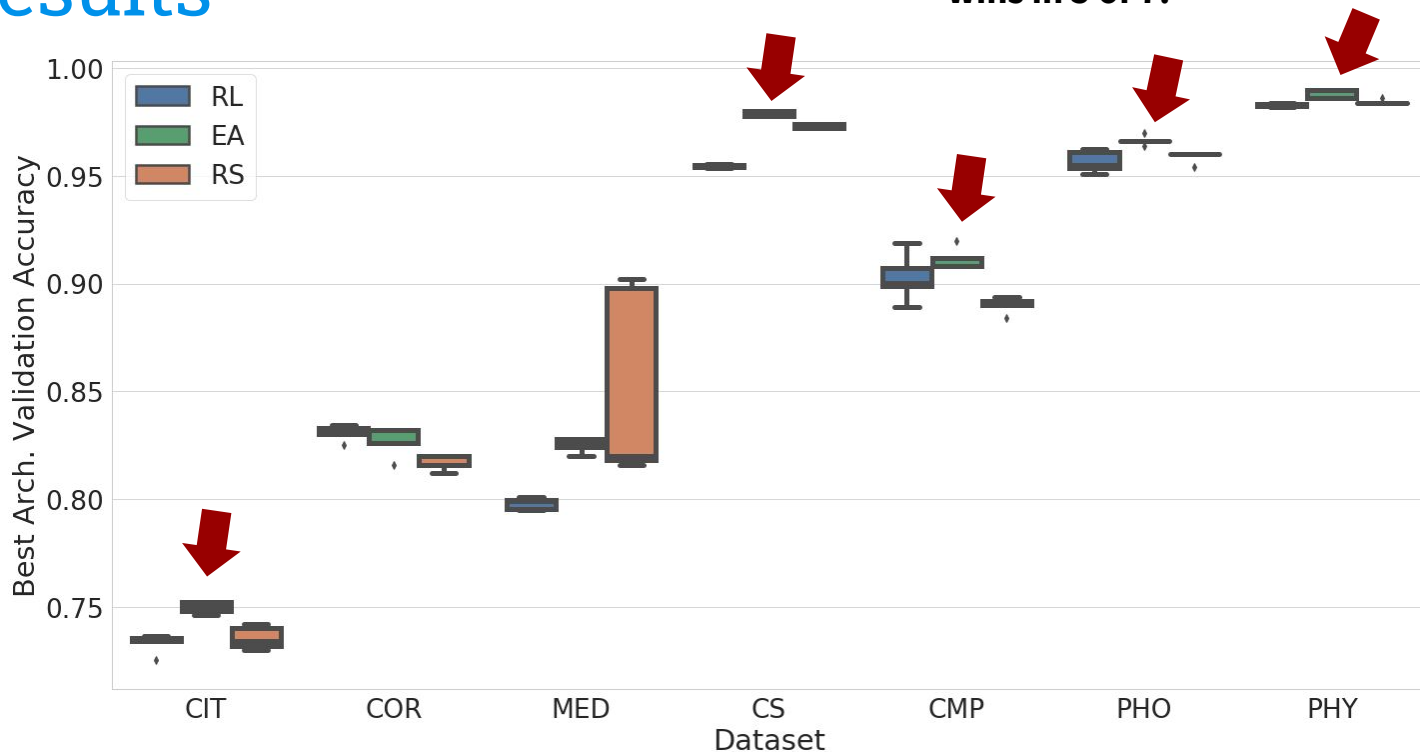
- ◎ All search methods run over 7 datasets, for 1000 iterations, using 5 different random seeds
- ◎ Dataset split: 500 validation nodes, rest for training (same as GraphNAS' paper)
- ◎ Code (and additional results):
https://github.com/mhnnunes/nas_gnn

Experimental Analysis

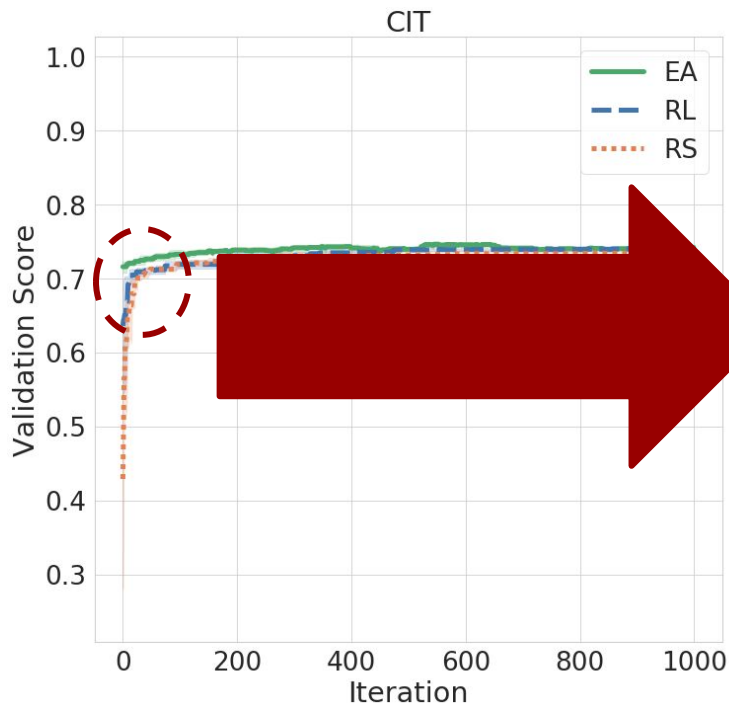
- ◎ Search methods settings:
 - RL: one-layer LSTM, 100 HU, ADAM opt., LR 3.5×10^{-4}
 - EA: Pop. size = 100, tournament size = 3 (best)
- ◎ Evaluate search methods in terms of best found child architecture **validation accuracy** and overall **runtime**

Results

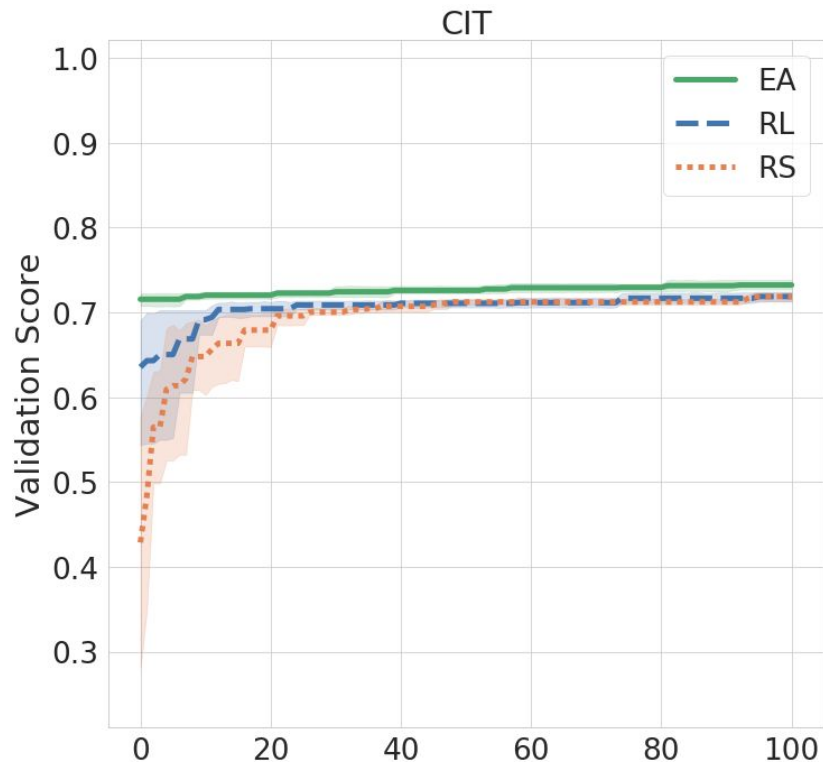
**Despite not being
statistically significant, EA
wins in 5 of 7!**



Results

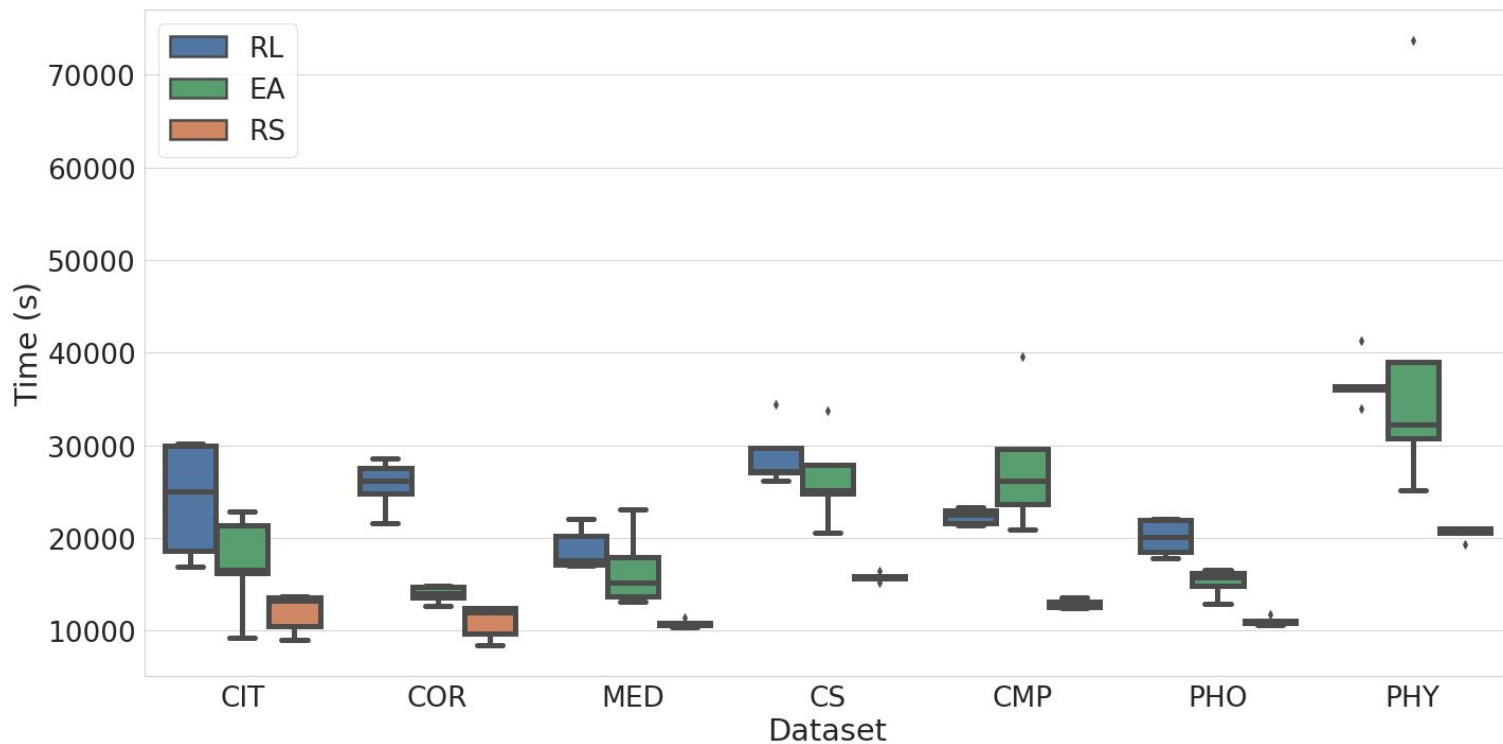


**All methods converge
early in the search!
< 100 iterations**

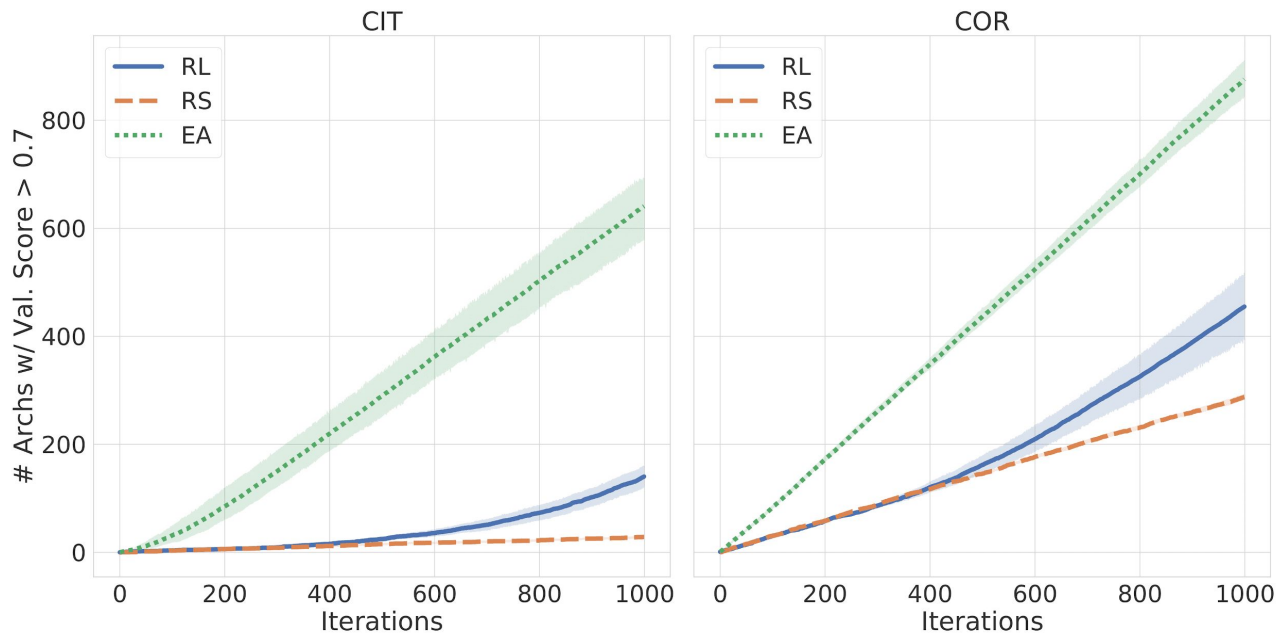


Results

**RS is faster in most cases,
with EA in second place!**



Results



EA consistently
generates and
evaluates high
accuracy
architectures!

Conclusions

- ◎ All three optimization methods **converge fast** and find **similarly good performing architectures**:
 - Neutrality?
- ◎ **EA** tends to generate better performing arch. than the other methods, and **RS** tends to be **fastest**



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