DARTS: Differentiable Architecture Search [1]

Recent trends in Automated Machine Learning (AutoML)

(IN2107, IN4954)

Technical University of Munich

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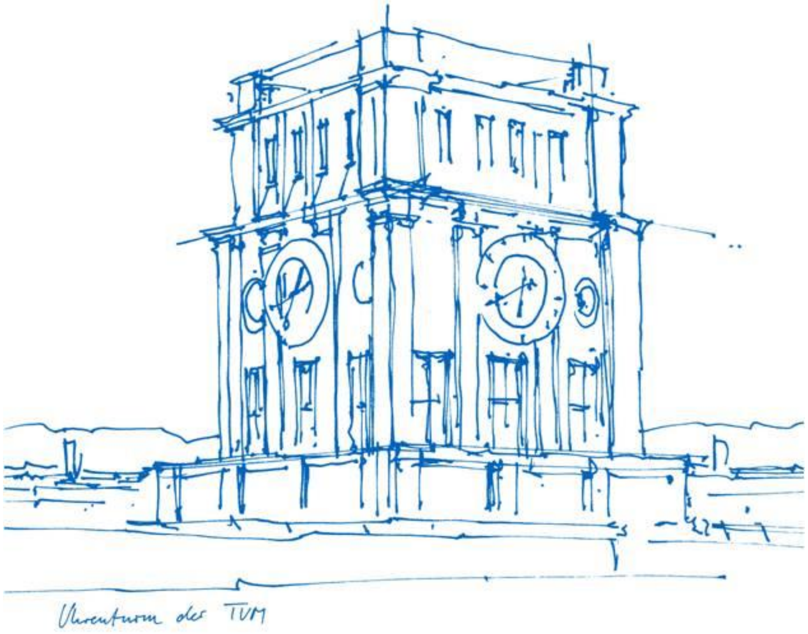
Munich, 09. June 2021



Quick Review

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NAS with RL [2]: Search for entire architecture

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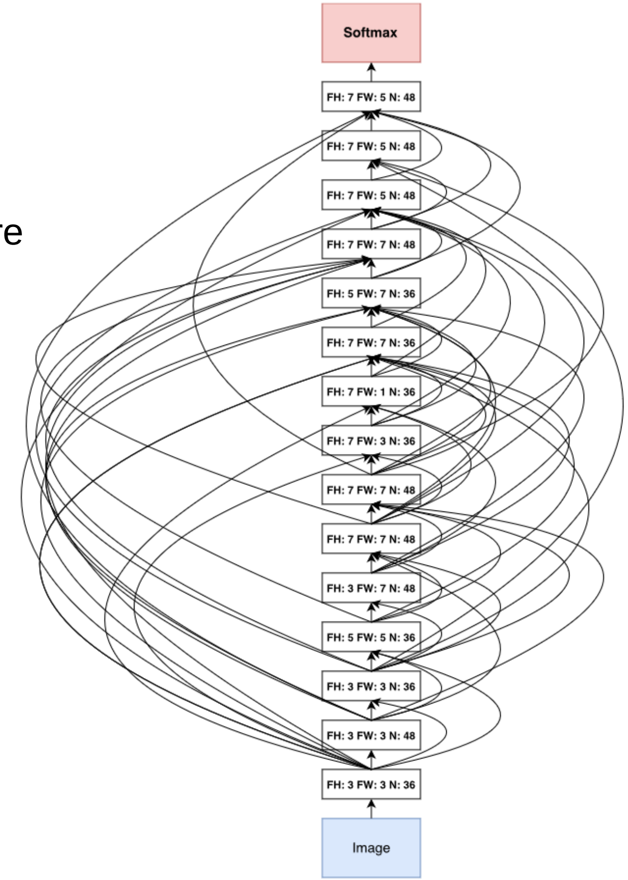

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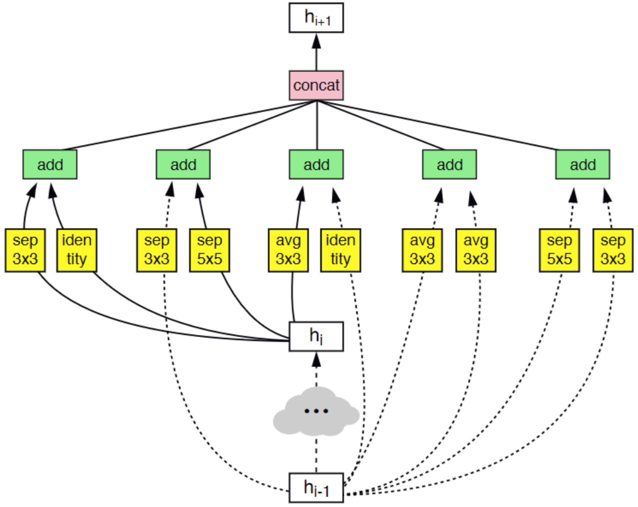
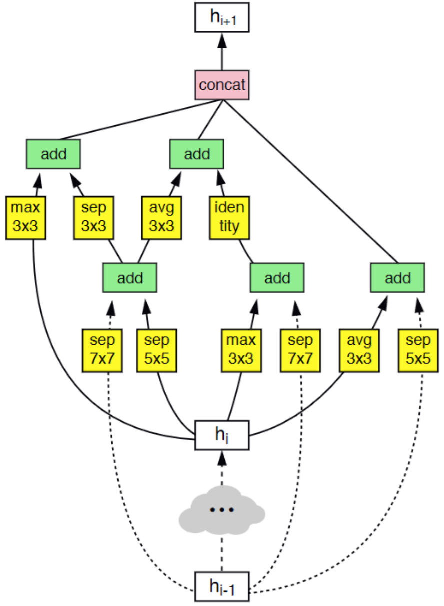


Normal Cell



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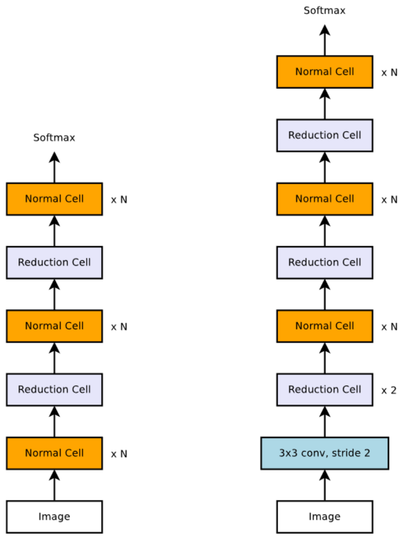
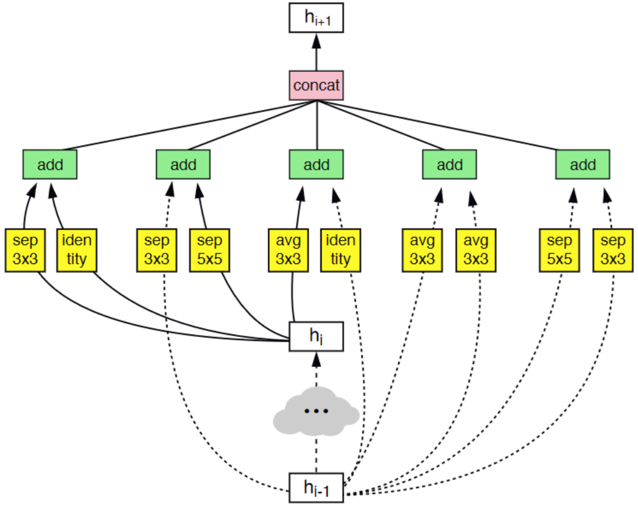


CIFAR10 Architecture

ImageNet Architecture



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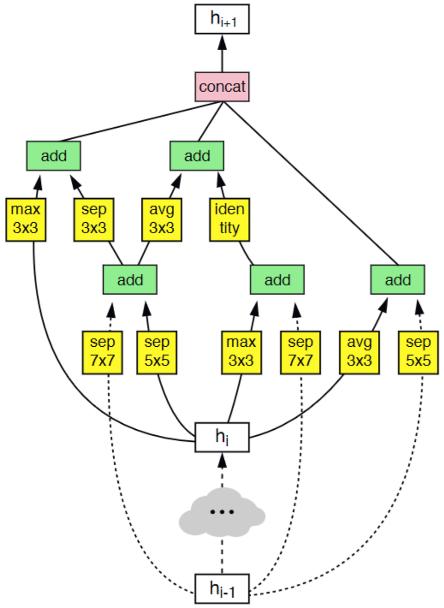

Reduction Cell

Motivation

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Search cost for CIFAR-10 architecture:

Architecture	Search method	GPU days	In years
NAS [2]	Reinforcement Learning (RL)	22400	61.3
NASNet [3]	RL	2000	5.5
AmoebaNet [4]	Evolutionary Algorithm	3150	8.6

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NASNet and AmoebaNet

- Good results
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Search space: discrete and **non-differentiable** → RL and Evolution

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Differentiable Architecture Search (DARTS)

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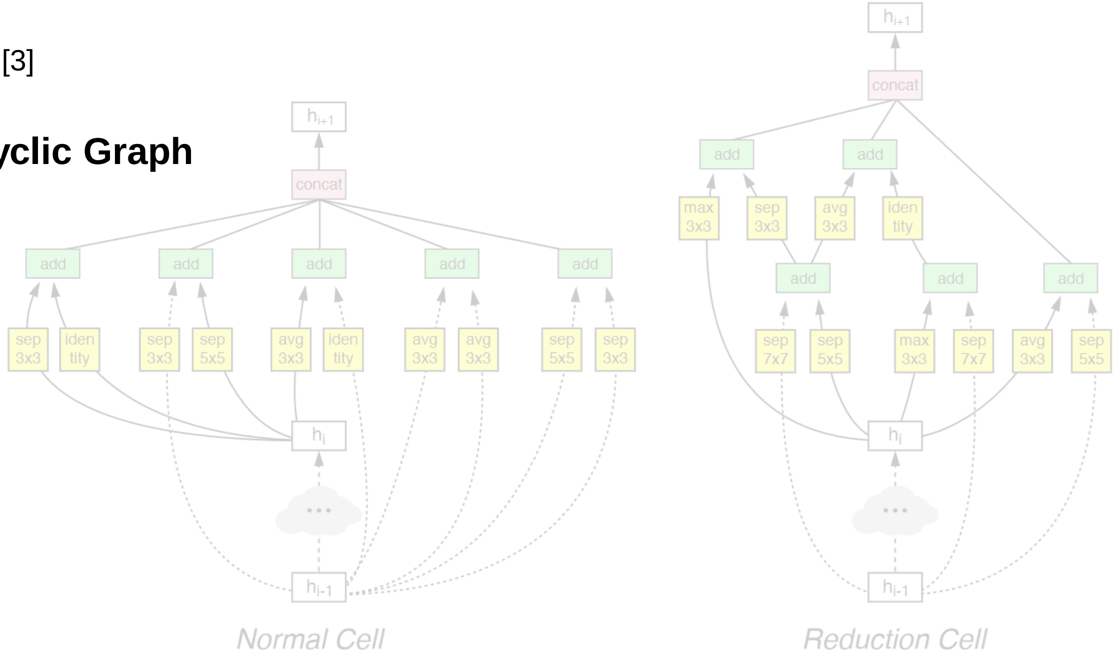
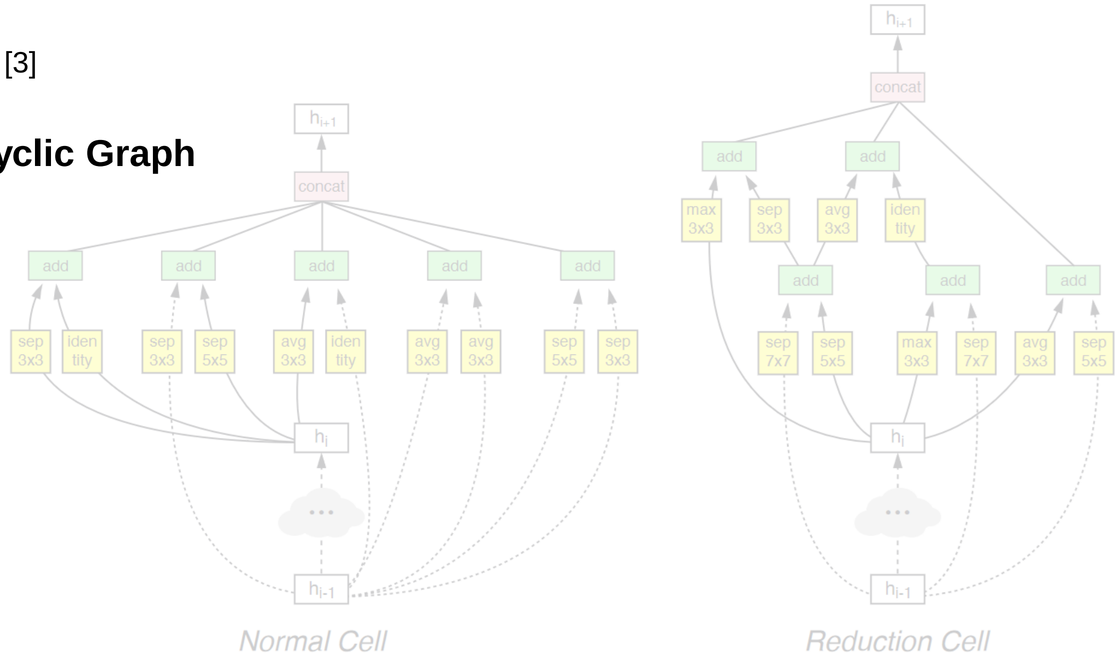


Search Space: NASNet [3]

Cell can be represented as a **Directed Acyclic Graph**

Nodes = latent representations
Edges = operations



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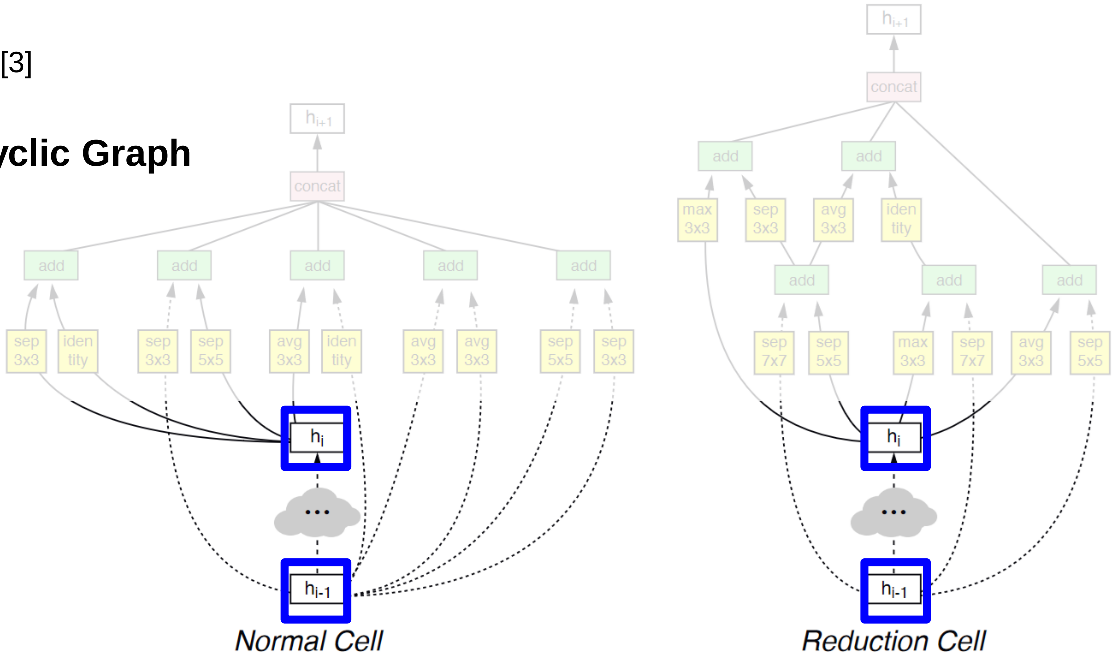
- 2 input nodes
  (outputs of 2 previous cells)



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Cell can be represented as a **Directed Acyclic Graph**

Nodes = latent representations
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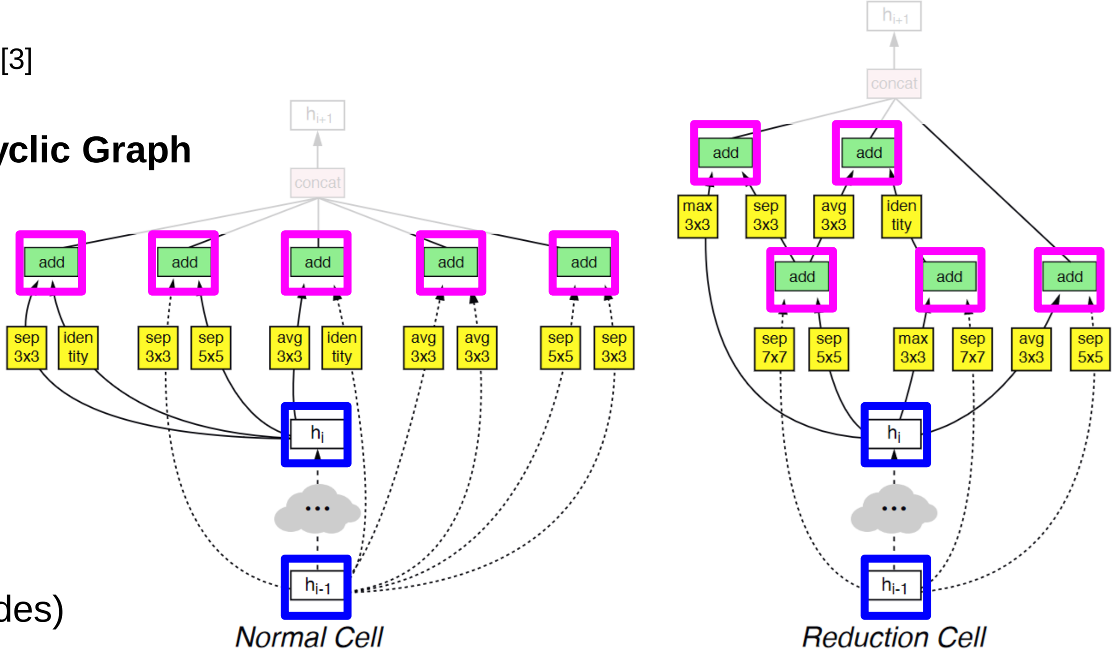
- 5 intermediate nodes
  (each with 2 edges from previous nodes)



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Cell can be represented as a **Directed Acyclic Graph**

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- 5 intermediate nodes
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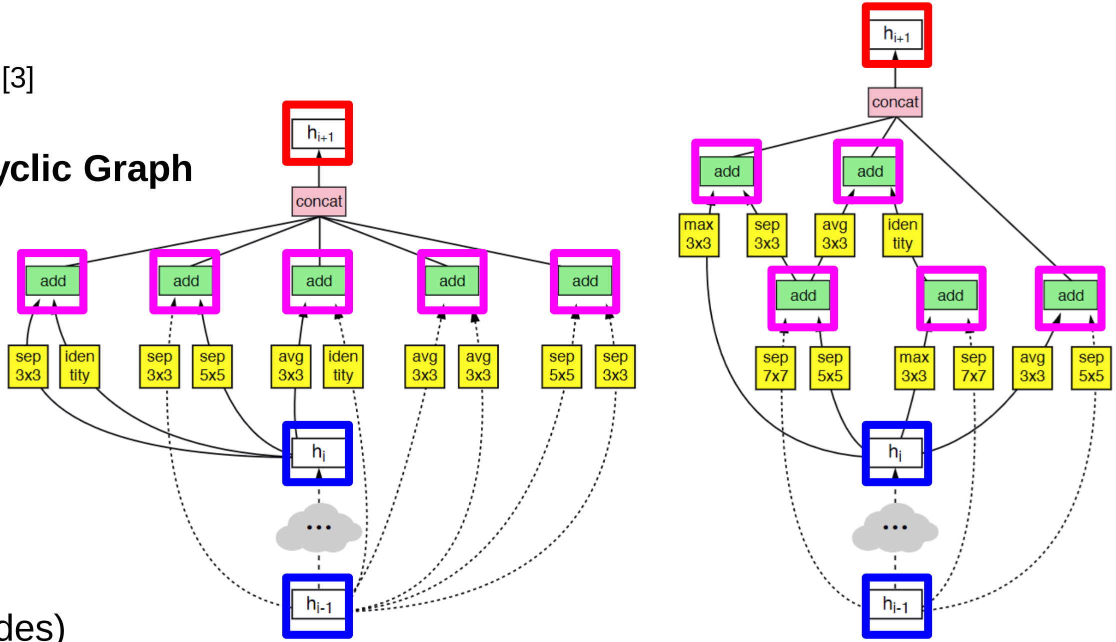
- 1 output node (concatenate all intermediate nodes)



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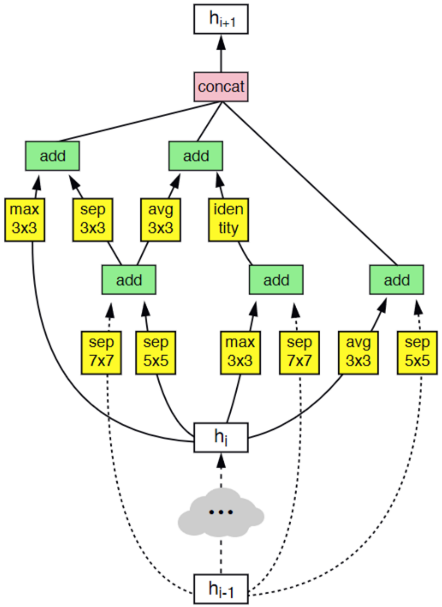
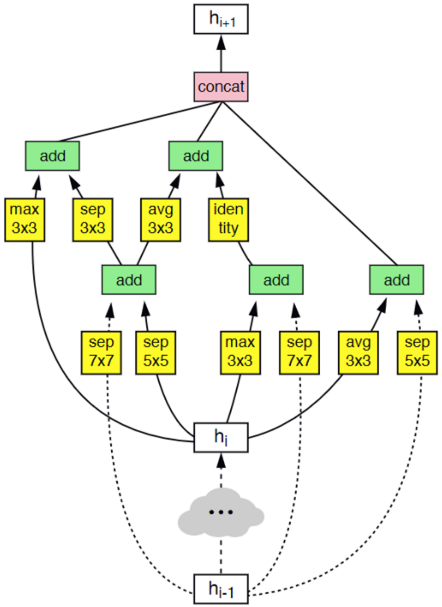


Search Space: DARTS [1]

Input and output nodes: fixed



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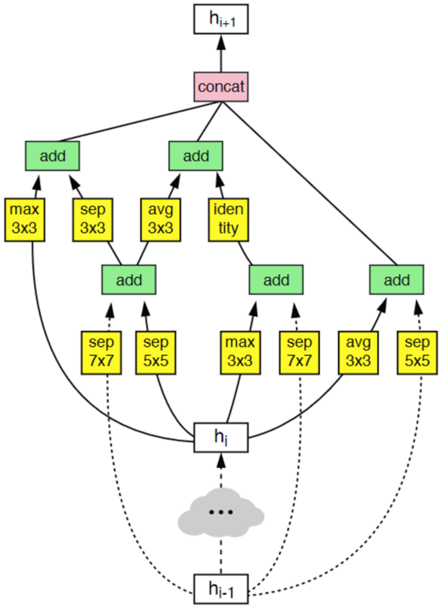
Intermediate nodes: fix to add



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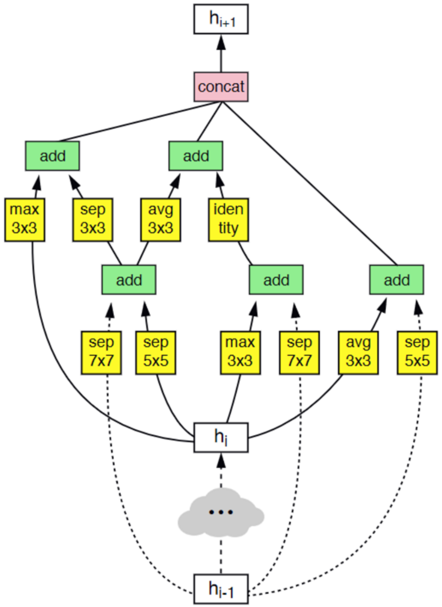

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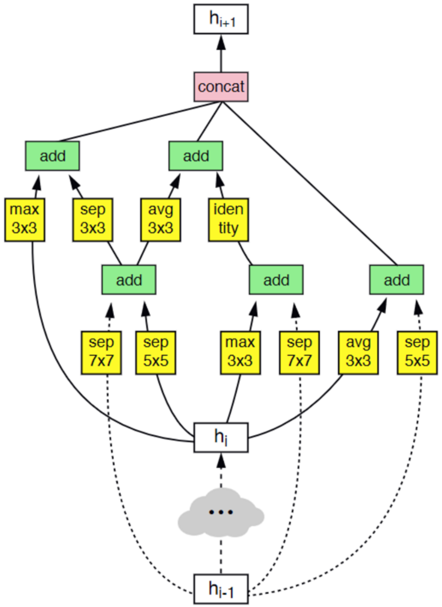

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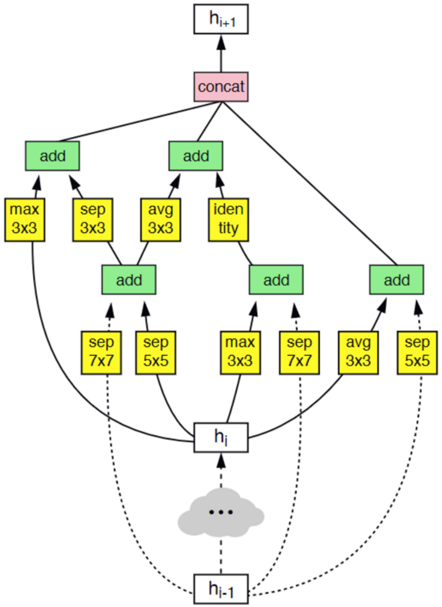
Learning cell = Learning edges

(which operations and which input nodes)



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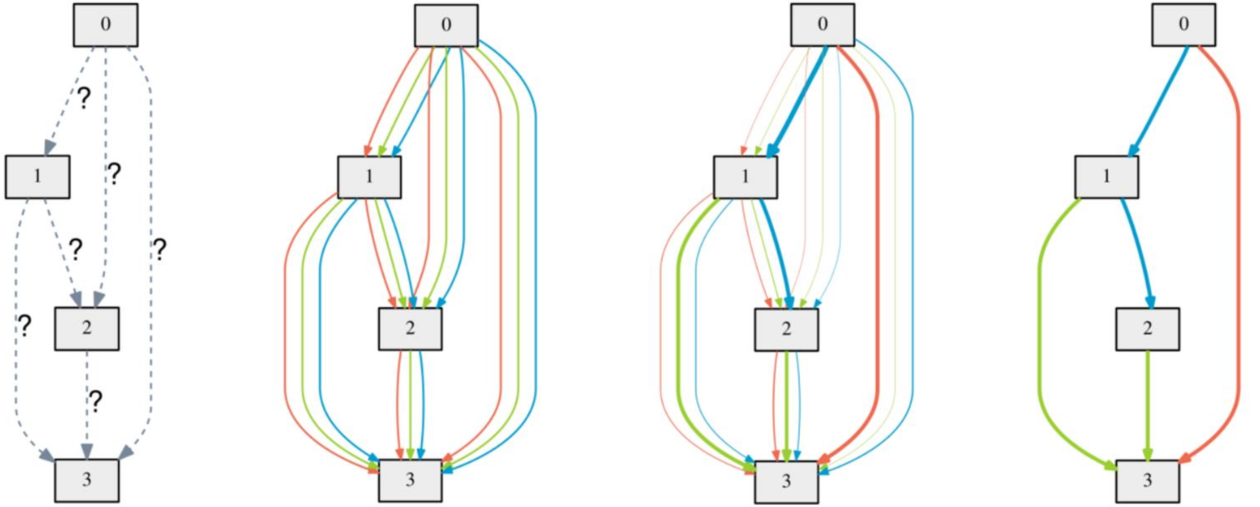

(a) (b) (c) (d)

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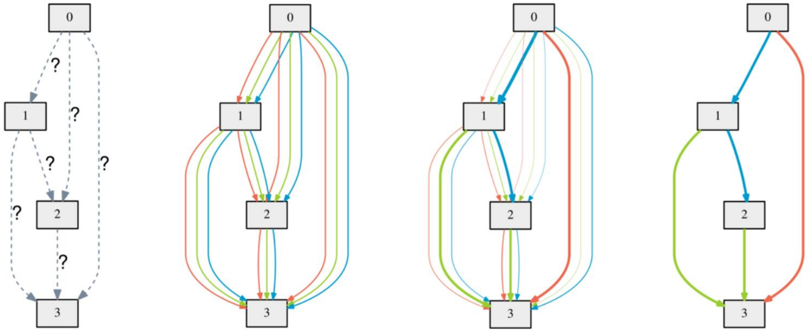

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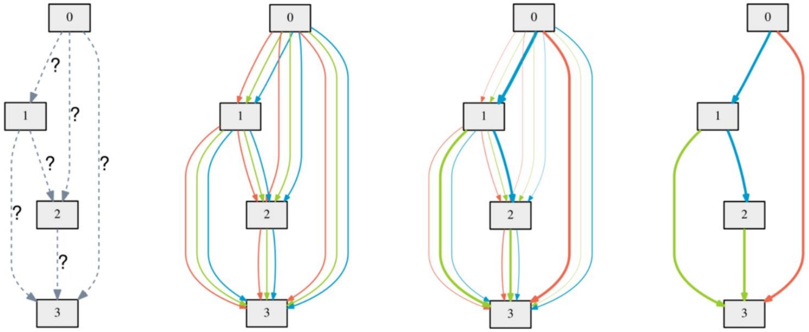
Search Space: Continuous Relaxation

Mixture of operations through softmax:

$$\bar{o}^{(i,j)}(x) = \sum_{o \in O} \frac{\exp(\alpha_o^{(i,j)})}{\sum_{o' \in O} \exp(\alpha_{o'}^{(i,j)})} o(x)$$



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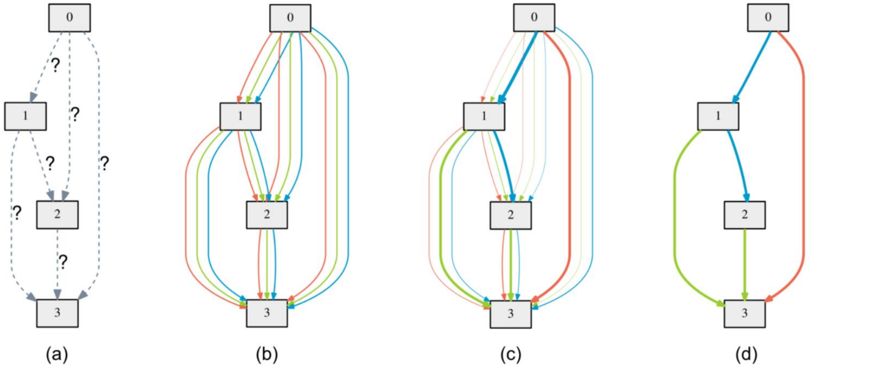

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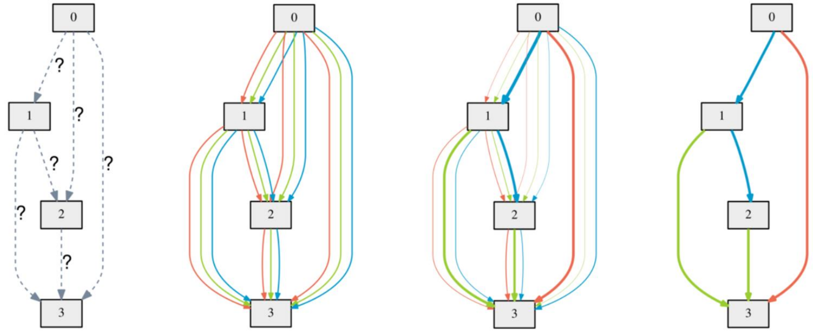

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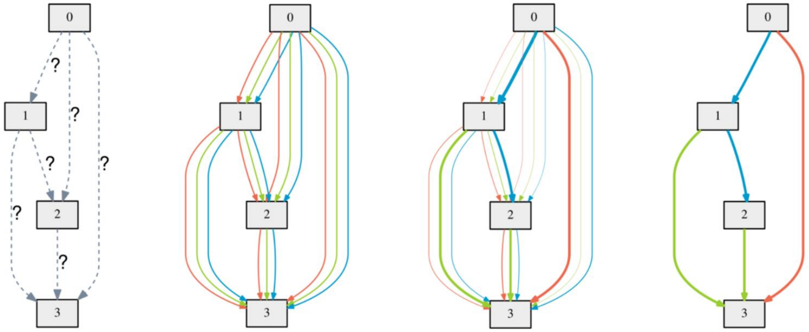

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$\alpha^{(i,j)}$: operation mixing weights for edge (i, j) – “encoding of the architecture”

Search Space: Specific Experiment Settings

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Convolutional cells:

- 7 nodes (2 input, 4 intermediate, 1 output)
- Inputs: outputs of the 2 previous cells (direct and skip connection)
- Operations (O): {{3×3, 5×5} separable convolutions, {3×3, 5×5} dilated separable convolutions, 3×3 max pooling, 3×3 average pooling, identity, **zero**}

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Recurrent cells:

- 12 nodes (2 input, 9 intermediate, 1 output)
- Inputs: current input and previous hidden state
- Operations (O): {linear transformations followed by one of {tanh, ReLU, sigmoid} activations, identity, **zero**}

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Goal: jointly learn architecture α and weights w

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s.t. $w^*(\alpha) = \mathrm{argmin}_w \, \mathcal{L}_{train}(w, \alpha)$

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Inner optimization: find best **weights** on **training** set (with current architecture) - Problematic!
Outer optimization: find best **architecture** on **validation** set

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Second order approximation (one gradient descent step):

$$\nabla_\alpha \mathcal{L}_{val}(w^*(\alpha), \alpha) \approx \nabla_\alpha \mathcal{L}_{val}(w - \xi \nabla_w \mathcal{L}_{train}(w, \alpha), \alpha)$$

Optimization: Approximation

With second order approximation still problematic: second order gradient (gradient of gradient)

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$$\nabla_\alpha \mathcal{L}_{val}(w^*(\alpha), \alpha) \approx \nabla_\alpha \mathcal{L}_{val}(w - \xi \nabla_w \mathcal{L}_{train}(w, \alpha), \alpha)$$

With chain rule, can be rewritten as:

$$\nabla_\alpha \mathcal{L}_{val}(w', \alpha) - \xi \nabla^2_{\alpha, w} \mathcal{L}_{train}(w, \alpha)\, \nabla_{w'} \mathcal{L}_{val}(w', \alpha)$$

where: $w' = w - \xi \nabla_w \mathcal{L}_{train}(w, \alpha)$

Optimization: Approximation

Second order gradient leads to very large matrix vector multiplication:

$\nabla^2_{\alpha,w}\mathcal{L}_{train}(w,\alpha)\ \nabla_{w'}\mathcal{L}_{val}(w',\alpha)$, where: $w' = w - \xi\ \nabla_w\mathcal{L}_{train}(w,\alpha)$

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Can be approximated by finite differences with step size ϵ (from multivariate Taylor expansion):

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$$\nabla^2_{\alpha,w}\mathcal{L}_{train}(w,\alpha)\ \nabla_{w'}\mathcal{L}_{val}(w',\alpha) \approx \frac{\nabla_\alpha\mathcal{L}_{train}(w^+,\alpha) - \nabla_\alpha\mathcal{L}_{train}(w^-,\alpha)}{2\epsilon}$$

where $w^{\pm} = w \pm \epsilon\ \nabla_{w'}\mathcal{L}_{val}(w',a)$

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Only one network is trained during search

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Algorithm 1: DARTS – Differentiable Architecture Search

Create a mixed operation $\bar{o}^{(i,j)}$ parametrized by $\alpha^{(i,j)}$ for each edge (i, j)
while *not converged* **do**
1. Update architecture α by descending $\nabla_\alpha \mathcal{L}_{val}(w - \xi \nabla_w \mathcal{L}_{train}(w, \alpha), \alpha)$
2. Update weights w by descending $\nabla_w \mathcal{L}_{train}(w, \alpha)$

Derive the final architecture based on the learned α.

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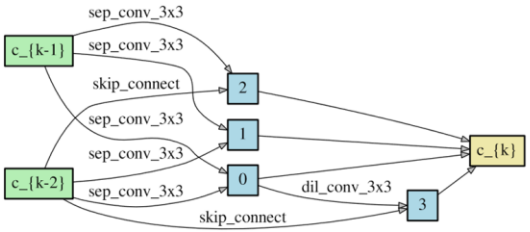
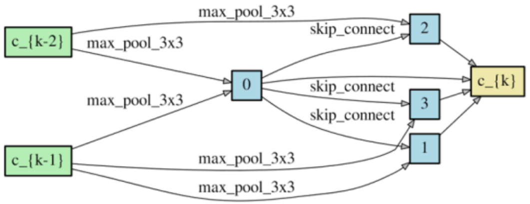
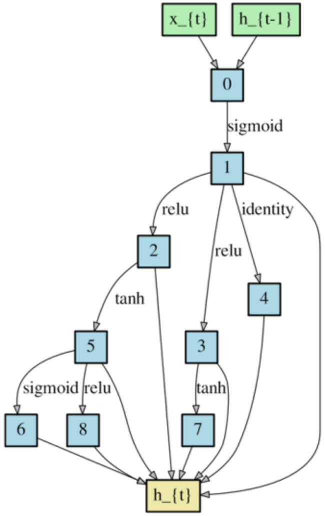
Resulting discrete cells:



Normal cell learned on CIFAR-10.



Reduction cell learned on CIFAR-10.



Recurrent cell learned on PTB.

Architecture Discretization

Each node gets assigned the top-k strongest edges = largest α's

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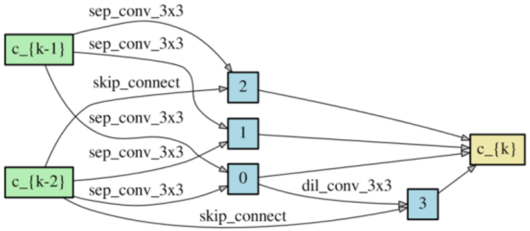
Resulting discrete cells:

(get retrained, do not keep the w's)



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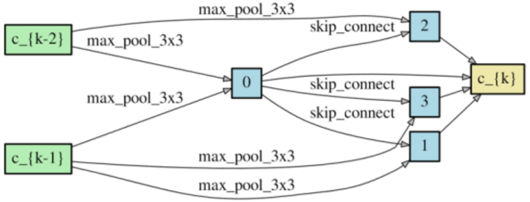

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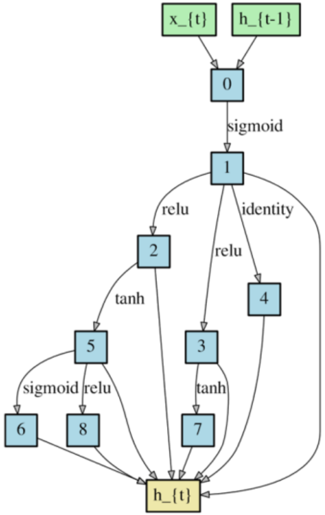

Recurrent cell learned on PTB.

Results

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Architecture searched on CIFAR-10	CIFAR-10 Test Error (%)
Random Search	3.29 ± 0.15
DARTS (**Coordinate descent on all data**)	4.16 ± 0.16
DARTS (**Gradient descent on all data**)	3.56 ± 0.10
DARTS (**bilevel** optimization, **first order approximation**)	3.00 ± 0.14
DARTS (**bilevel** optimization, **second order approximation**)	2.76 ± 0.09

Results: CIFAR-10

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Architecture	Test Error (%)	Params (M)	Search cost (GPU days)	Search method
DenseNet-BC	3.46	25.6	-	manual
NASNet-A + cutout	2.65	3.3	2000	RL
AmoebaNet-B + cutout	2.55 ± 0.05	2.8	3150	evolution
DARTS (second order) + cutout	2.76 ± 0.09	3.3	4	gradient-based

(DARTS repeated 4 times with different initializations, best one selected)

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Convolutional cells (searched on CIFAR-10)

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Recurrent cells (searched on PTB)

- State-of-the-art results on PBT
- Less transferrable to WT2

Conclusion

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Much more efficient architecture search, can be performed without massive resources

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Only mentioned by authors, no quantification given

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- *P-DARTS [7], FairDARTS [8], DARTS+ [9], sharpDARTS [10]* (better performance)
- *PC-DARTS [11]* (reduce computational cost, use larger batch size, better performance)
- *UnNAS [12]* (unsupervised NAS, without human annotated labels)
- *ProxylessNAS [13]* (reduce computational cost, search on target dataset, low latency objective, better performance)

- And many, many more…

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RL and evolution direction:

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MnasNet [5] → multi-objective optimization: maximize accuracy and minimize FLOPS

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RL and evolution direction:

MnasNet [5] → multi-objective optimization: maximize accuracy and minimize FLOPS
Was used for *EfficientNet* [6]

Questions?

References

[1] DARTS: Differentiable Architecture Search. Liu et al. (2018).

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