Continual and Multi-Task Architecture Search

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UNC NLP

Introduction

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Continual Learning

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Continual Learning	**Model parameters evolve and adapt when trained sequentially on a new task**
Multi-Task Learning	**Given multiple tasks in parallel, learns a generalizable cell structure**

Continual Learning

Definition: Continual learning (CL) is the ability to learn continually from a stream of data, building on what was learnt previously, while being able to *reapply*, *adapt* and *generalize* it to new situations.

[Donahue et al., 2014; Zeneke et al., 2017; Yoon et al., 2018]

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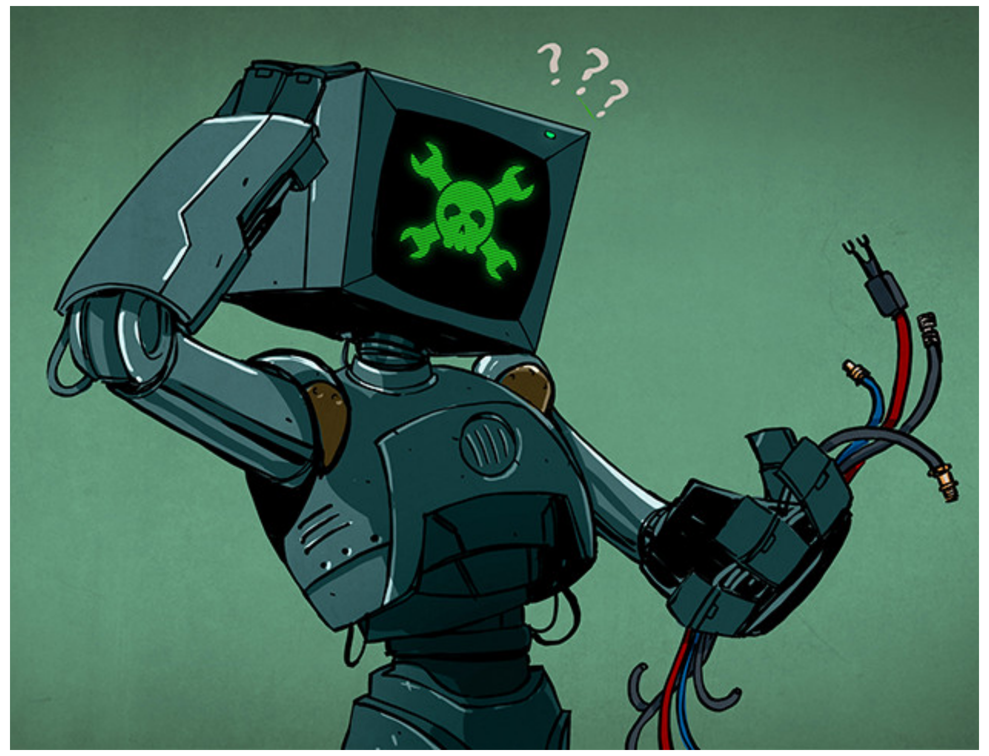

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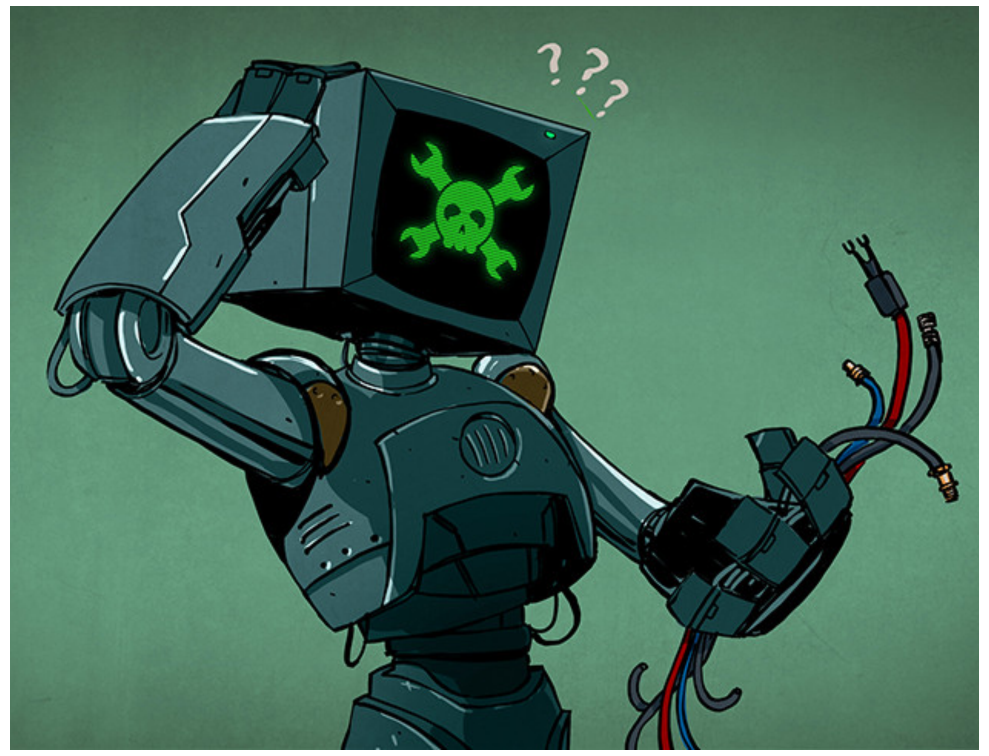
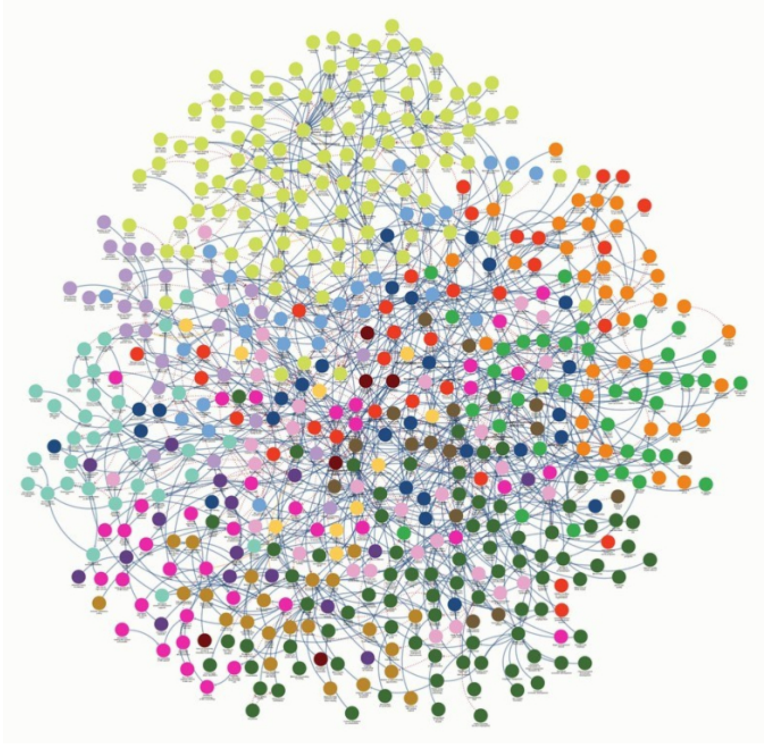


Bounded System Size



[Donahue et al., 2014; Zeneke et al., 2017; Yoon et al., 2018]

Previous Work

Regularization to penalize functional or shared parameters' change
[Razavian et al., 2014; Li and Hoiem, 2017; Hinton et al., 2015; Jung et al., 2016; Kirk- patrick et al., 2017; Donahue et al., 2014; Yosinski et al., 2014]

Copying the previous task and augmenting with new task's features
[Rusu et al., 2016]

Intelligent synapses to accumulate task-related information
[Zeneke et al., 2017]

Dynamically expandable network based on incoming new data
[Yoon et al., 2018]

Idea!

Leverage Neural Architecture Search!

Continual Architecture Search (CAS): continually evolve the model parameters during the sequential training of several tasks by leveraging neural architecture search.

[Donahue et al., 2014; Zeneke et al., 2017; Yoon et al., 2018]

NAS

Neural Architecture Search (NAS): has been recently introduced for automatic learning of the model structure for the given dataset/task.

- Shown good improvements on image classification and language modeling
- Computationally feasible NAS approaches:
  - Tree-structured search space
  - ϵ-greedy exploration

[Zoph & Le, 2017; Baker et al., 2017; Negrinho & Gordon, 2017]

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Efficient Neural Architecture Search (ENAS): A weight-sharing strategy among search parameters **[Pham et al., 2018]**

[Zoph & Le, 2017; Baker et al., 2017; Negrinho & Gordon, 2017]

ENAS

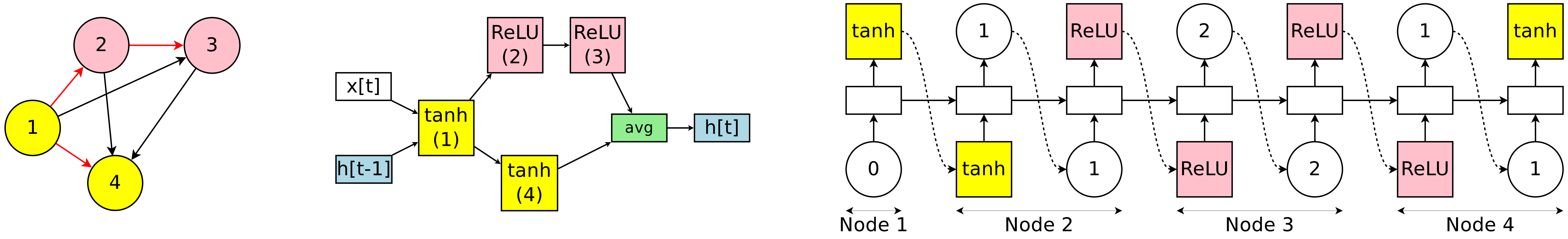


Figure: An example of a recurrent cell in our search space with 4 computational nodes. *Left:* The computational DAG that corresponds to the recurrent cell. The red edges represent the flow of information in the graph. *Middle:* The recurrent cell. *Right:* The outputs of the controller RNN that result in the cell in the middle and the DAG on the left. Note that nodes 3 and 4 are never sampled by the RNN, so their results are averaged and are treated as the cell's output.

[Pham et al., 2018]

ENAS

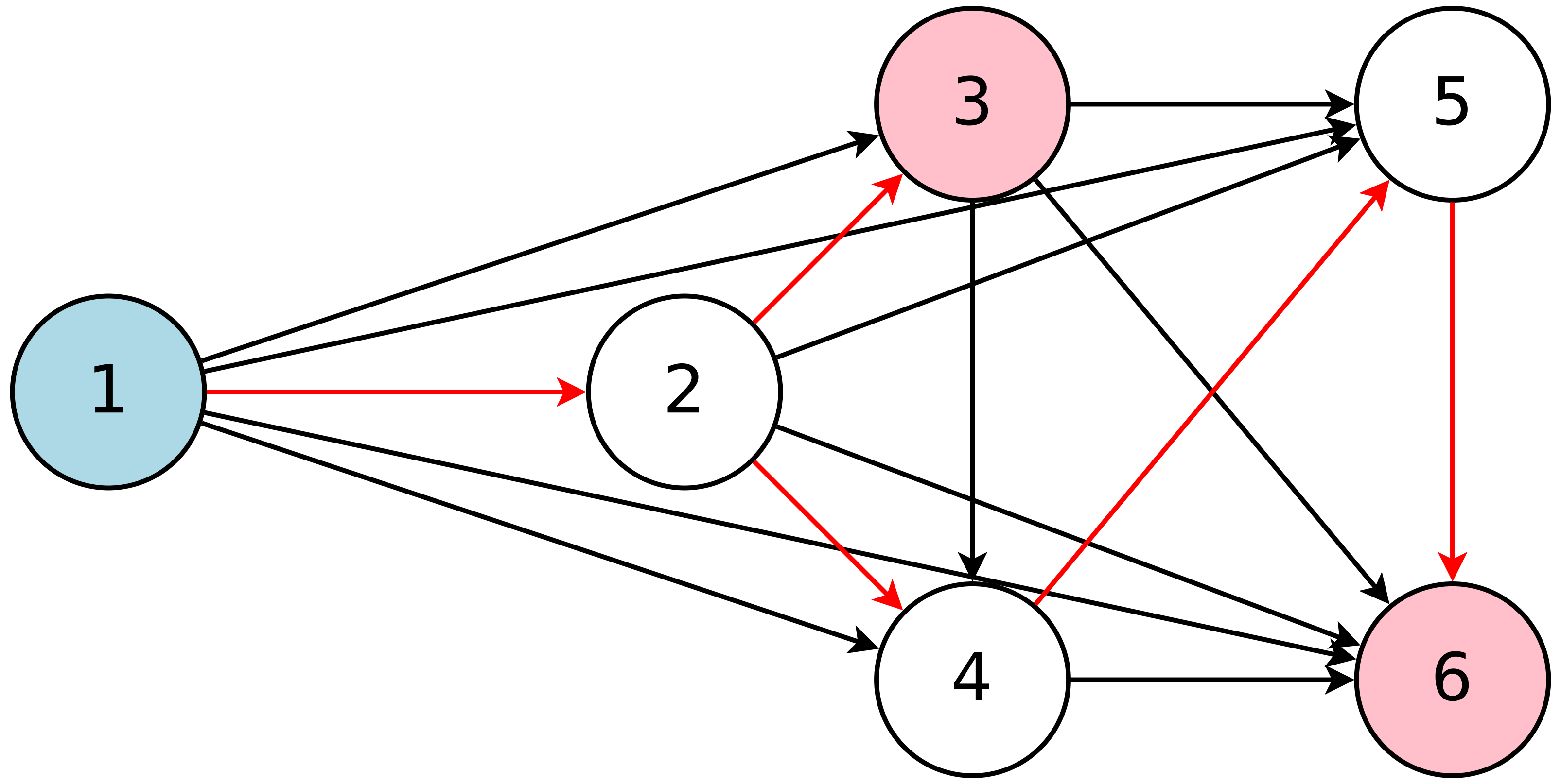
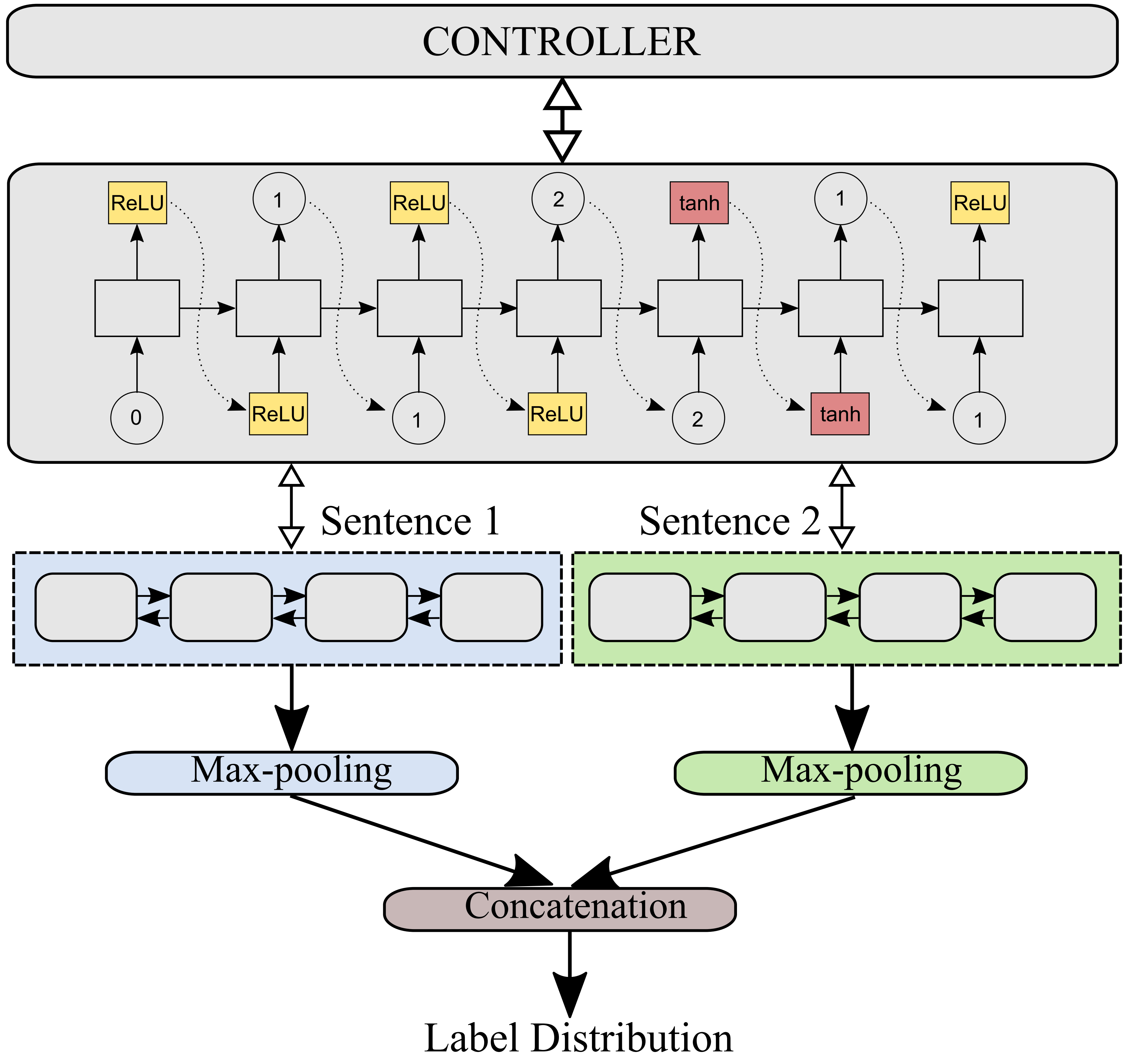


Figure: The graph represents the entire search space while the red arrows define a model in the search space, which is decided by a controller. Here, node 1 is the input to the model whereas nodes 3 and 6 are the model's outputs.

[Pham et al., 2018]

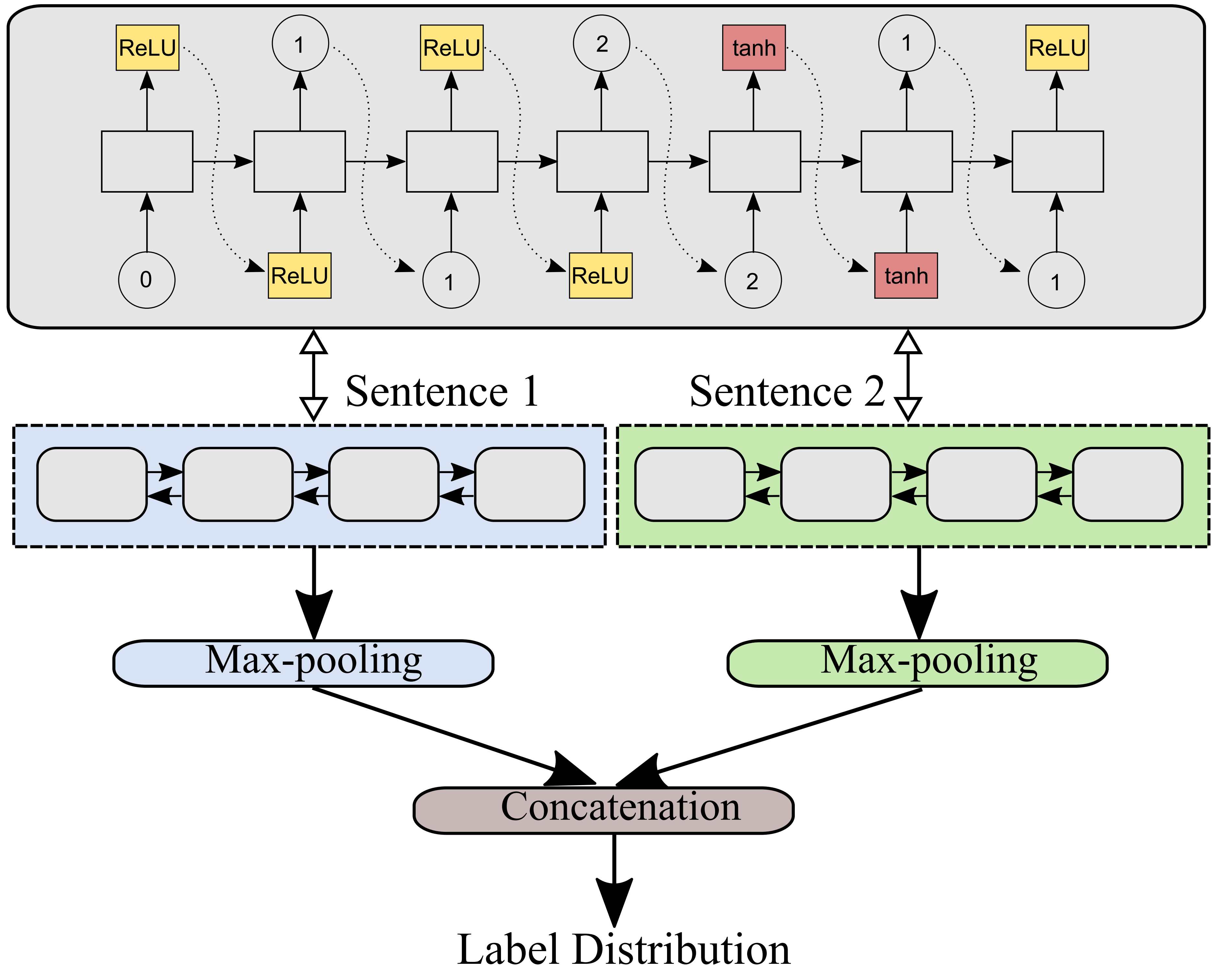
ENAS for Text Classification



Stage1:

- Controller samples a cell structure and use the task's performance as feedback
- Controller learns optimal cell structure

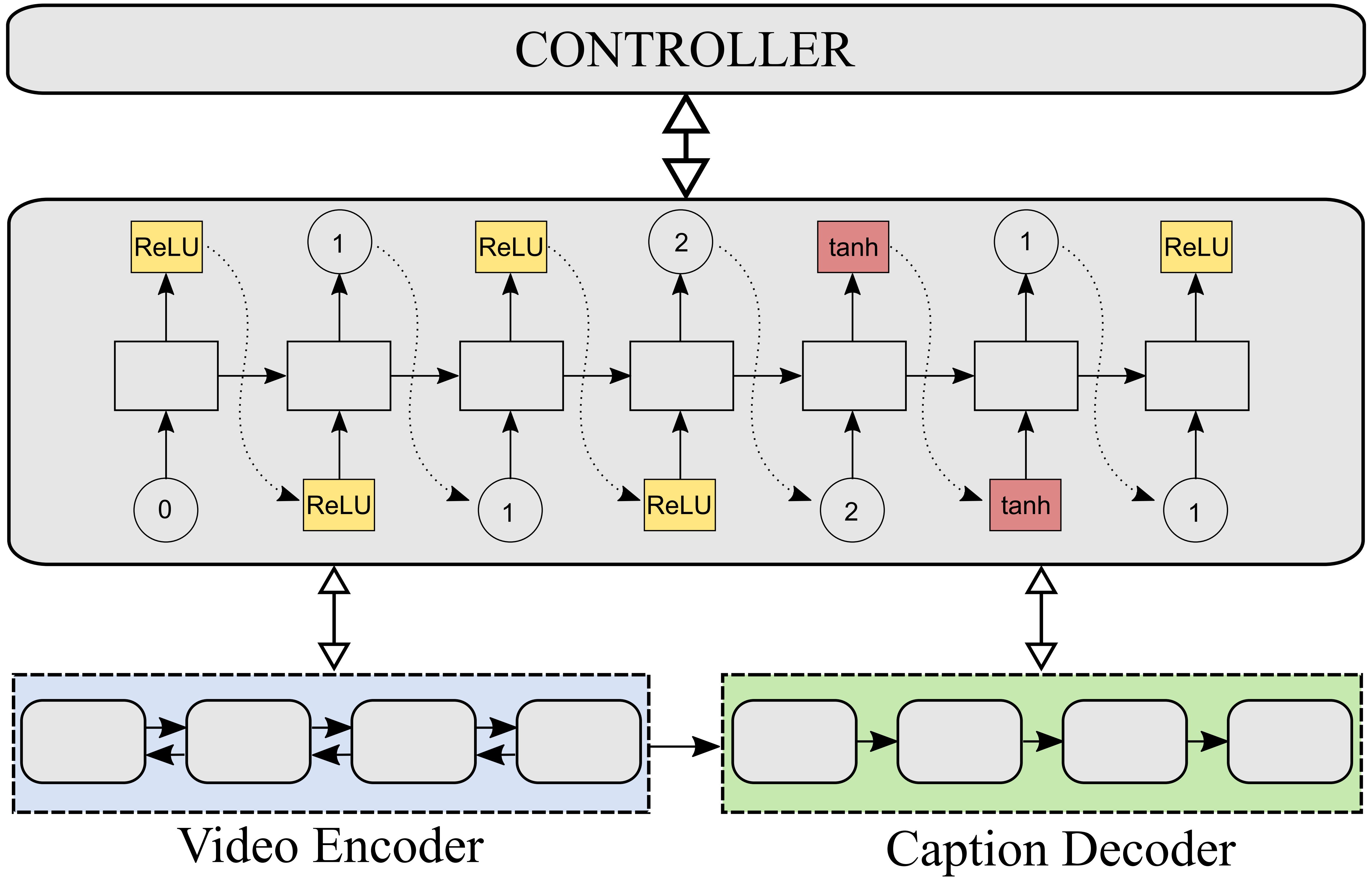
ENAS for Text Classification



Stage2:

- Retrain the model using the learned optimal cell structure in stage-1

ENAS for Sequence Generation



Continual Architecture Search (CAS)

Task1 (dataset d_1)

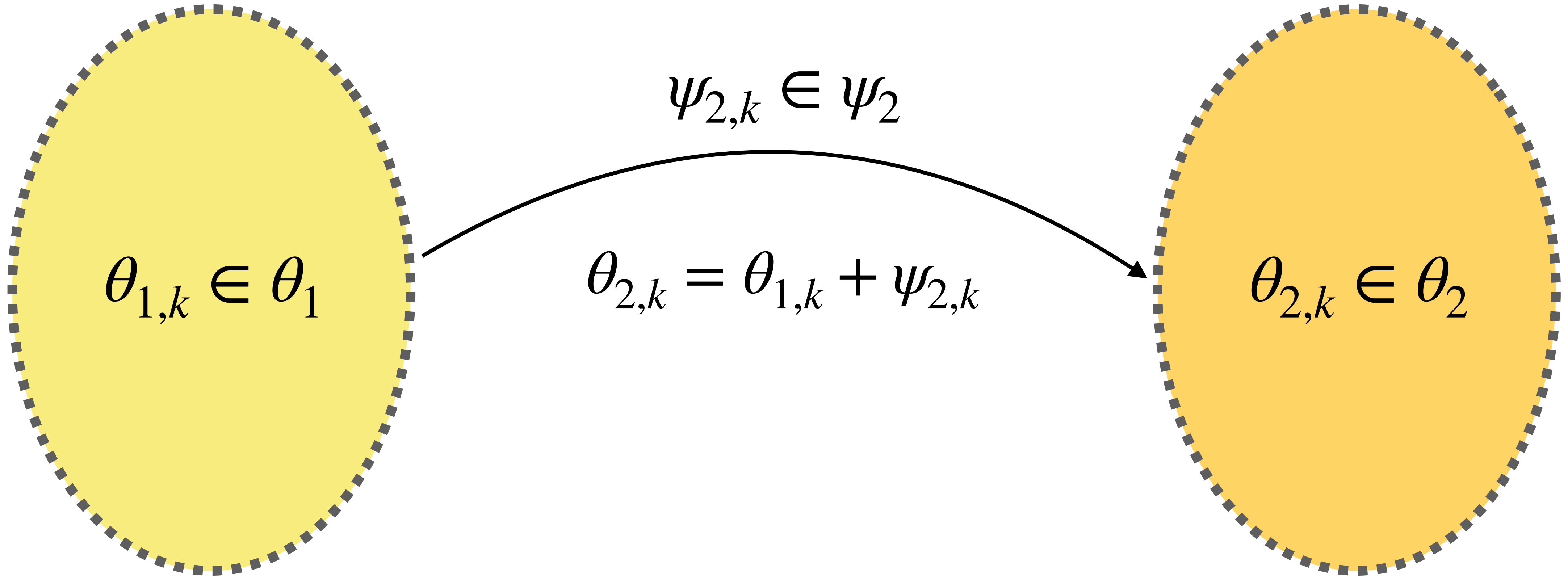
$\theta_{1,k} \in \theta_1$

Task2 (dataset d_2)

$\theta_{2,k} \in \theta_2$

Continual Architecture Search (CAS)

Task1 (dataset d_1) **Task2** (dataset d_2)



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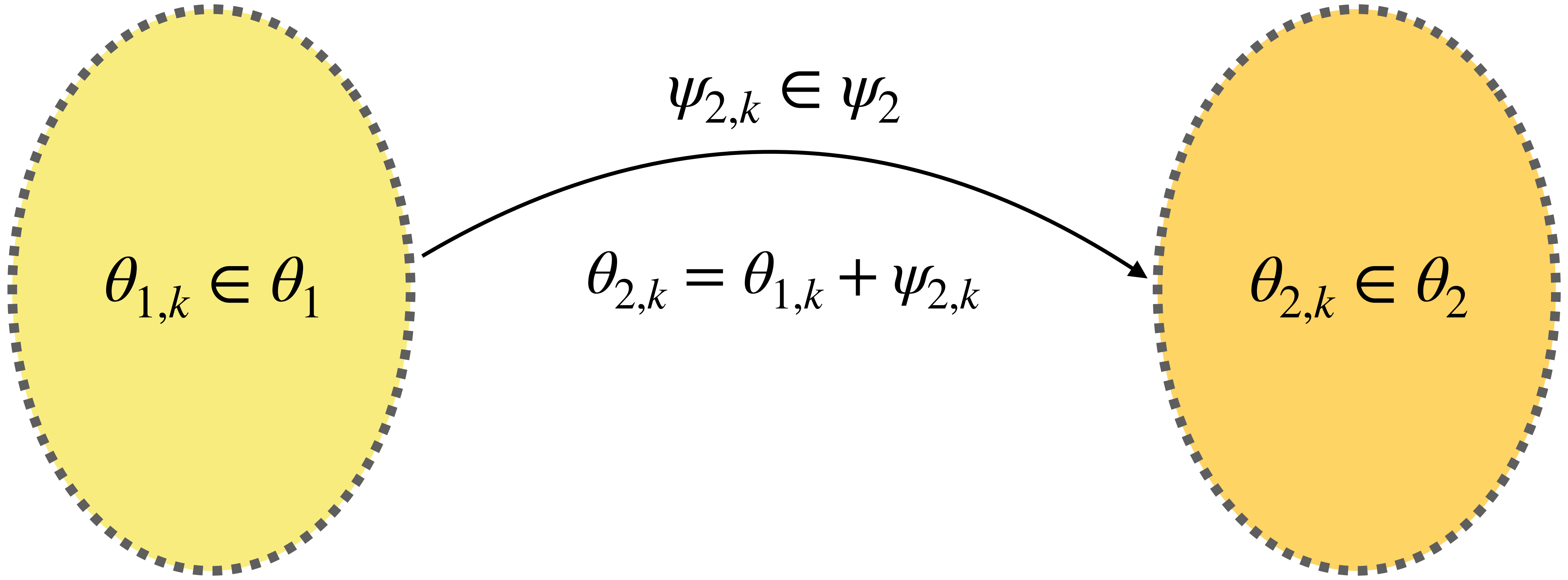

θ_1 are block-sparse in nature

[Scardapane et al., 2017]

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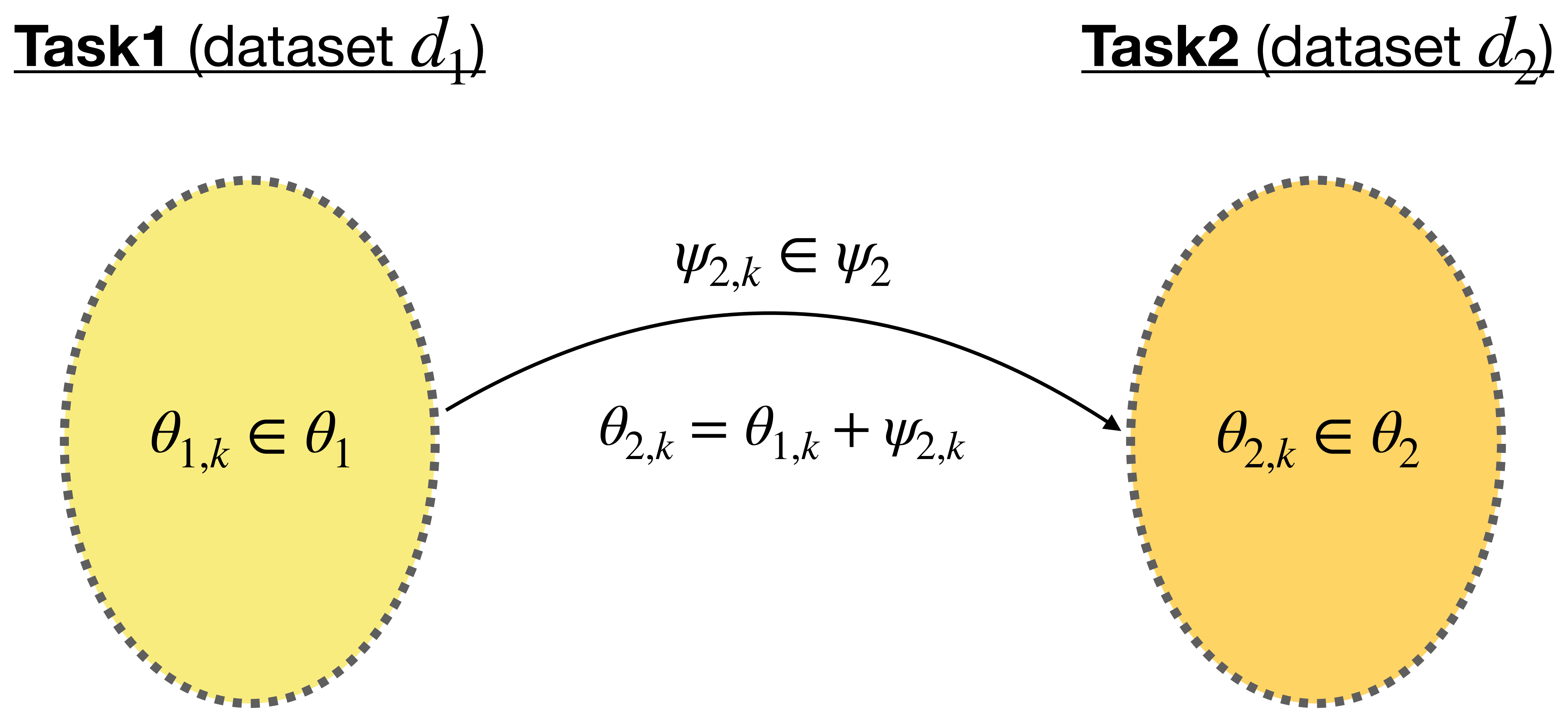
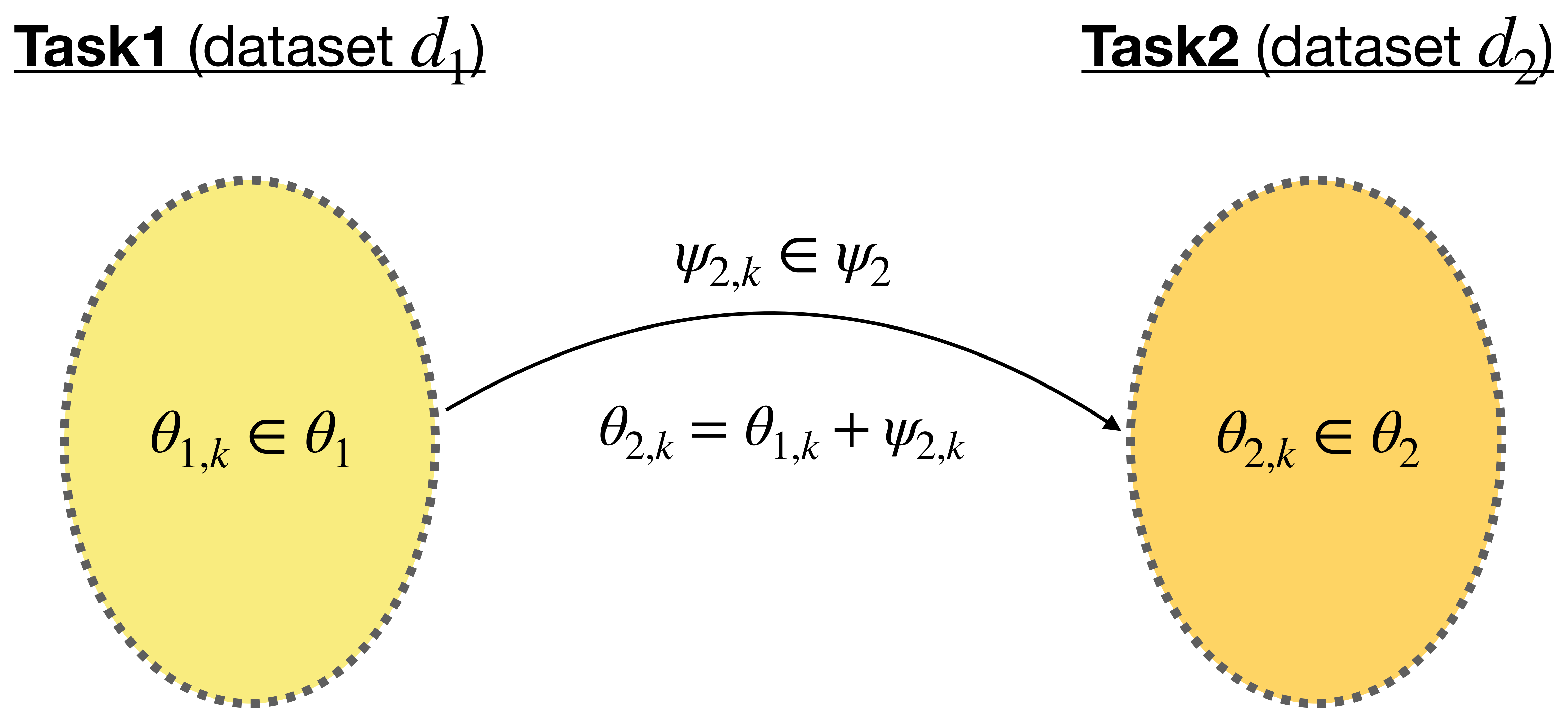


θ_1 are block-sparse in nature

ψ_2 is orthogonal to θ_1

[Bousmalis et al., 2016; Scardapane et al., 2017]

Continual Architecture Search (CAS)



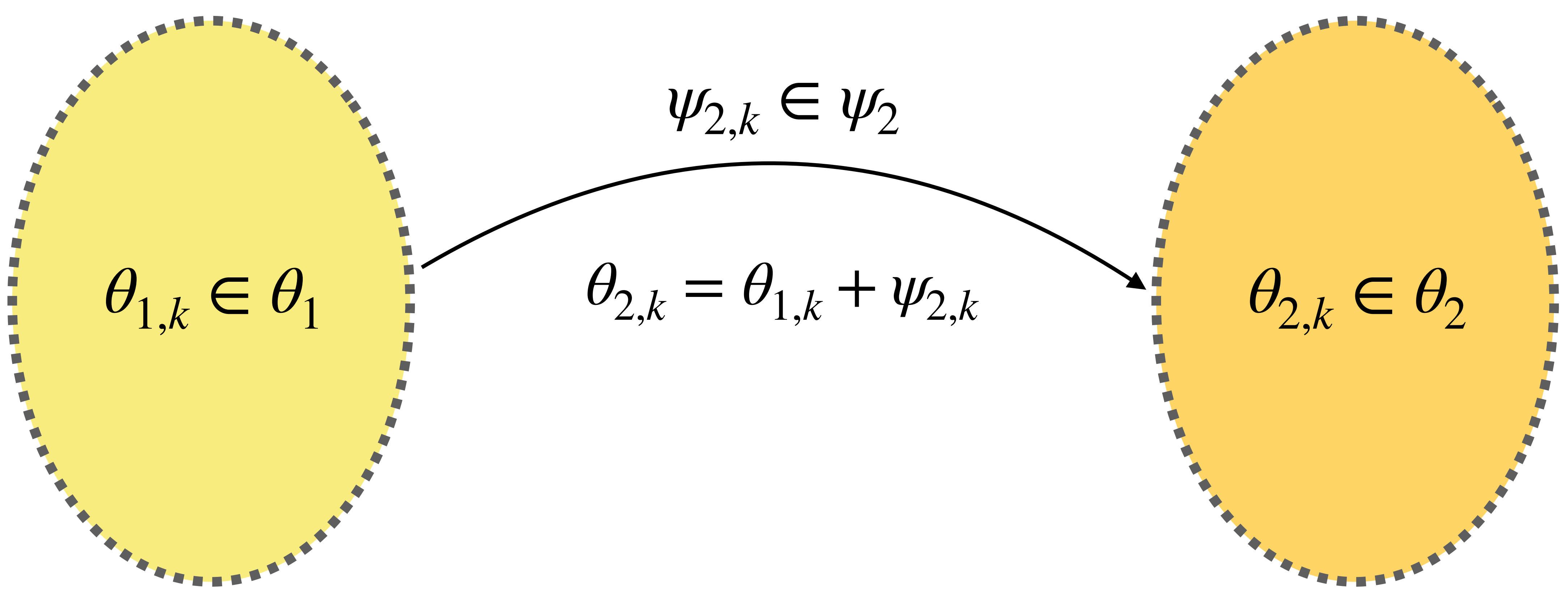
Condition 1: *When training the model on dataset* d_1, *we constrain the model parameters* $\theta_{1,k} \in R^{m\times n}$ *to be sparse, specifically, to be block sparse, i.e., minimize*

$$\sum_{i=1}^{m} |(||\theta_{1,k}[i,:]||_2)|_1$$

[Scardapane et al., 2017]

Continual Architecture Search (CAS)

Task1 (dataset d_1) **Task2** (dataset d_2)

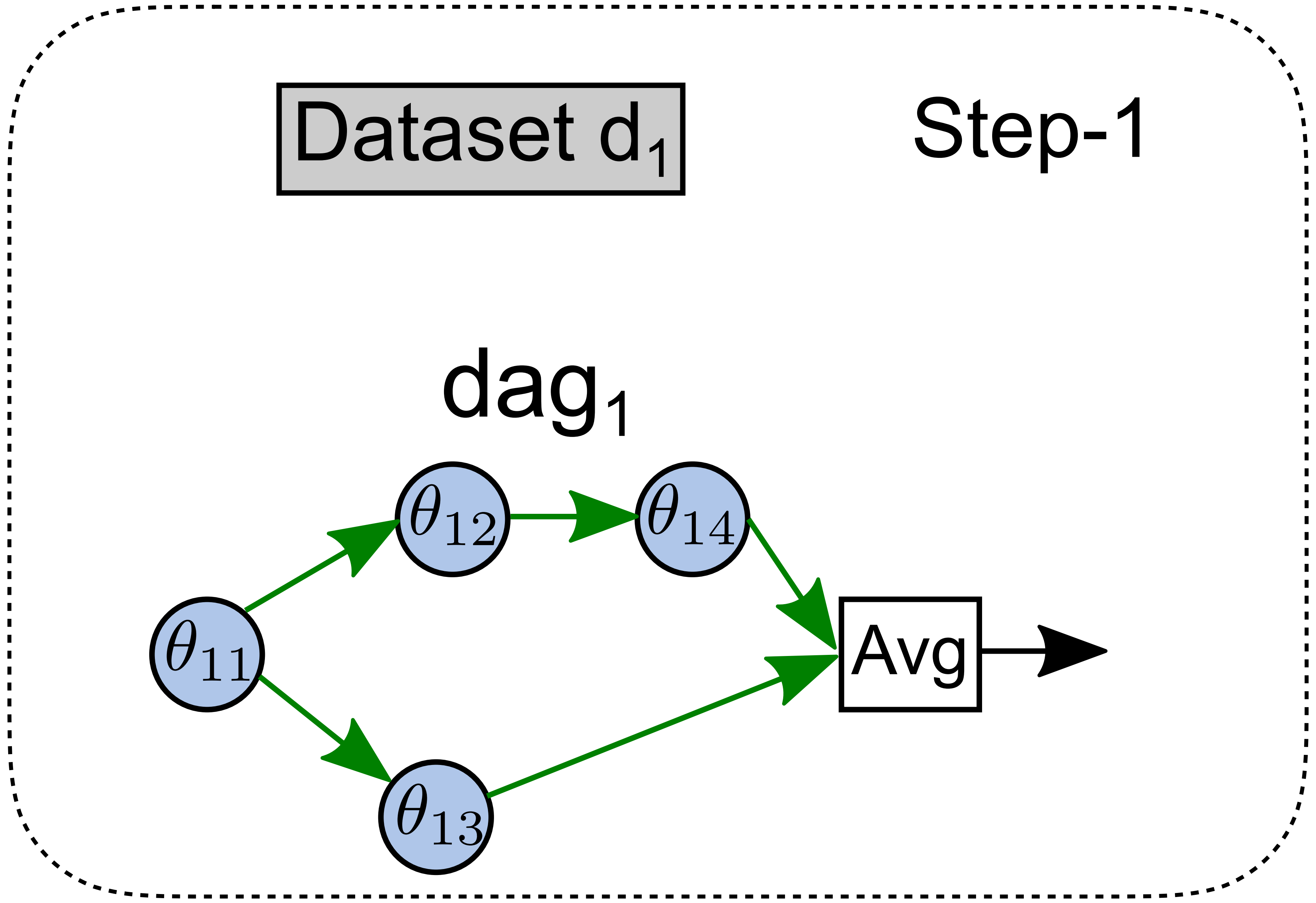


Condition 2: *When training the model on dataset d_2, we start from $\theta_{1,k}$, keep it constant, and update $\psi_{2,k}$ such that:*

1. $\psi_{2,k}$ *is block sparse, i.e.,* $\sum_{i=1}^{m} |(||\psi_{2,k}[i,:]||_2)|_1$.
2. $\theta_{1,k}$ *and* $\psi_{2,k}$ *are orthogonal.*

[Bousmalis et al., 2016]

CAS Step-1



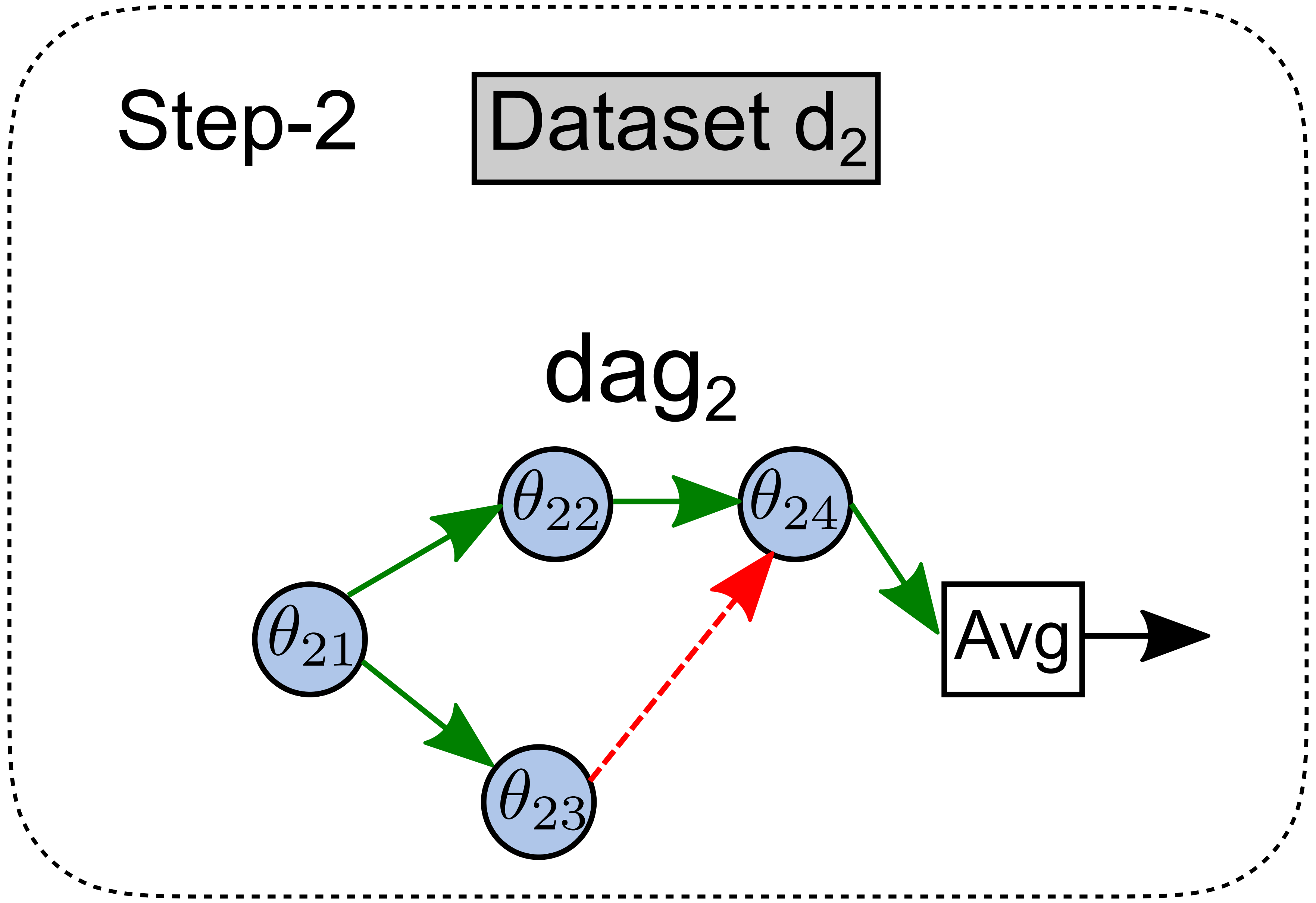
Train on Dataset d_1

Apply Condition 1

Learn parameters θ_1 and cell structure dag_1

R. Pasunuru & M. Bansal

CAS Step-2



Train on Dataset d_2 and initialize the parameters with θ_1

Apply Condition 2

Learn parameters θ_2 and cell structure dag_2

CAS Evaluation

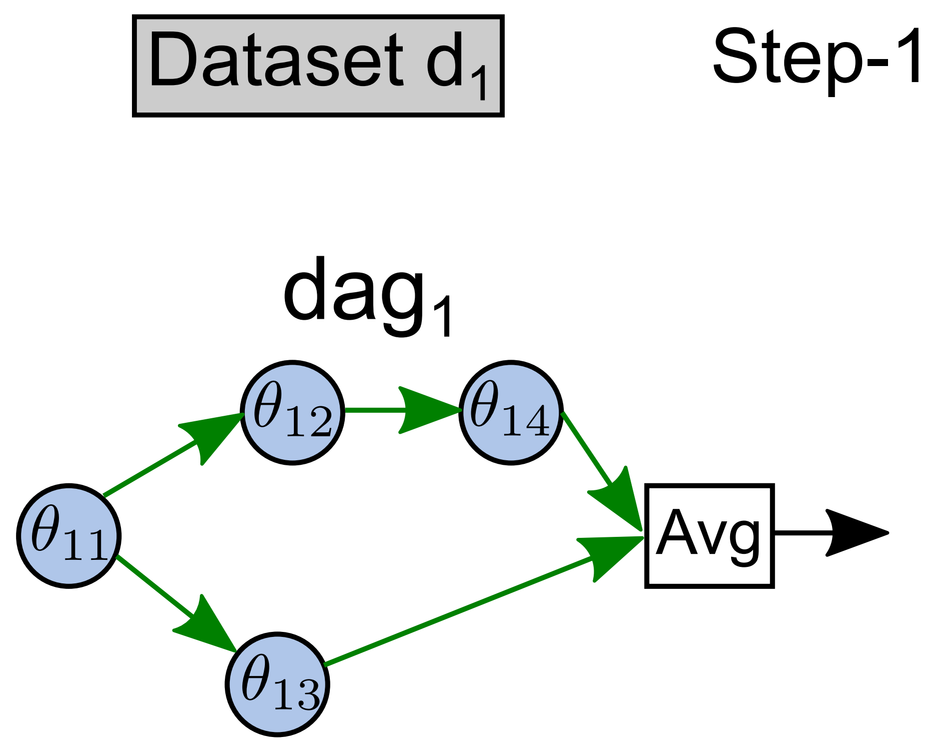


Figure: Continual architecture search (CAS) approach: green, solid edges (weight parameters) are shared, newly-learned edges are represented with red, dashed edges.

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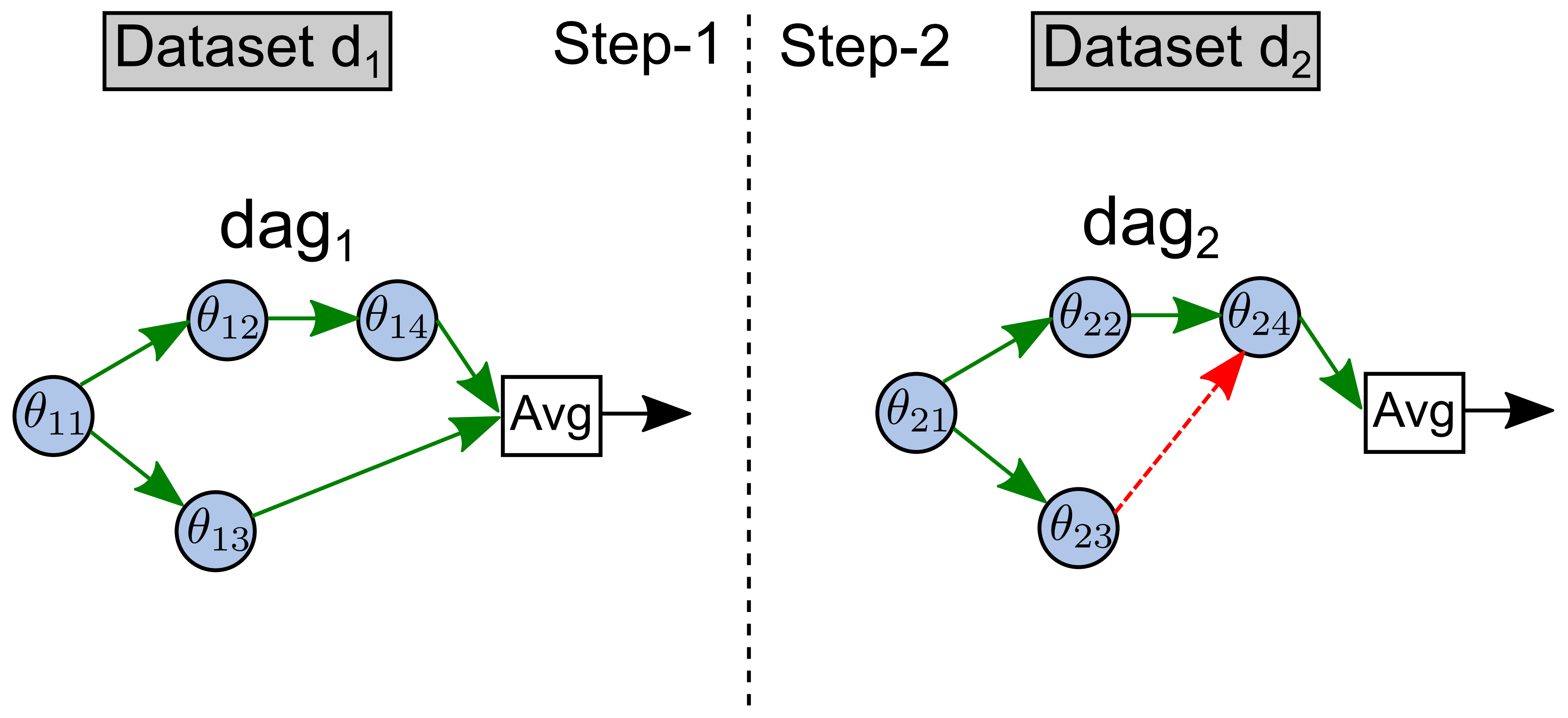

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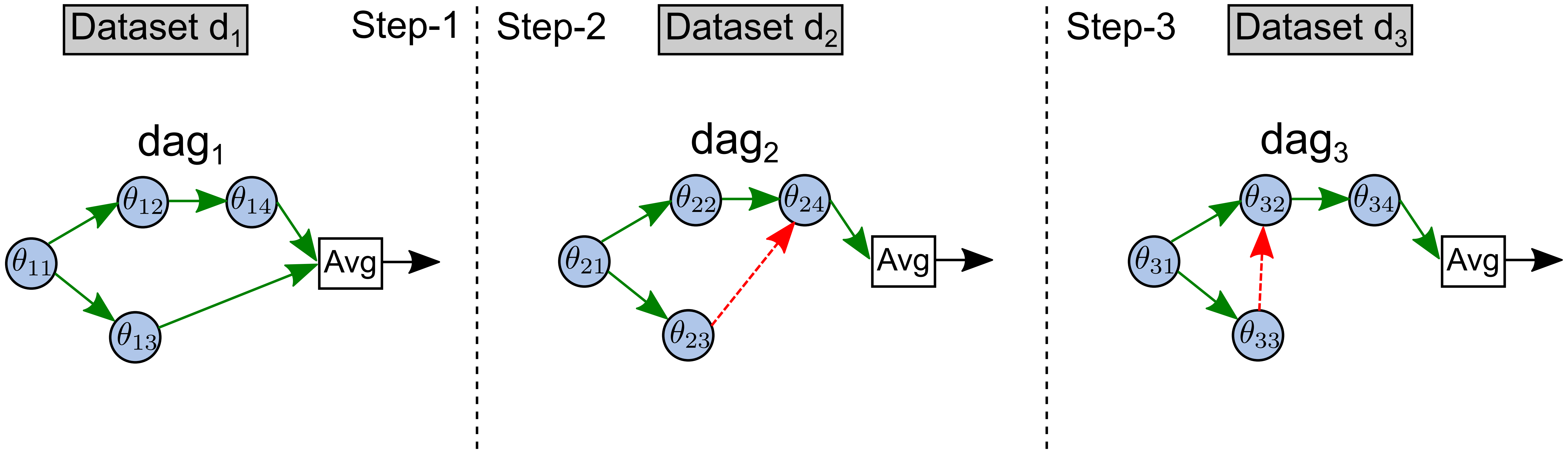

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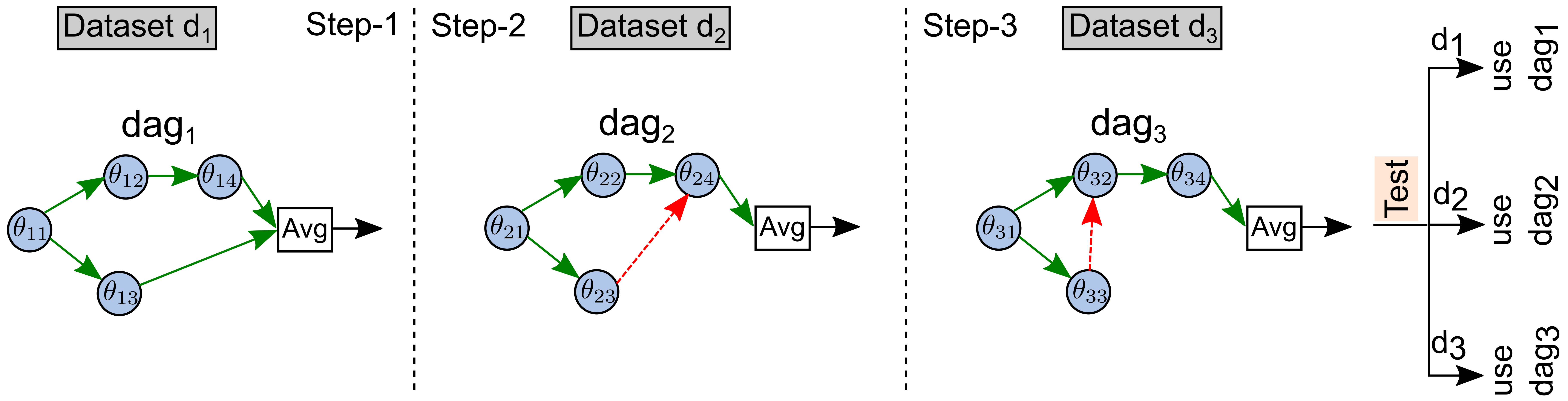

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Generalizable NAS on Sequential Tasks

CAS Results on Text Classification

Models	QNLI	RTE	WNLI
PREVIOUS WORK			
BiLSTM+ELMo (2018)	69.4	50.1	65.1
BiLSTM+ELMo+Attn (2018)	61.1	50.3	65.1
BASELINES			
Baseline (with ELMo)	73.2	52.3	65.1
ENAS (Architecture Search)	74.5	52.9	65.1

Table: Test results on GLUE tasks for various models: Baseline, ENAS, and CAS (continual architecture search). The CAS results maintain statistical equality across each step.

[Dagan et al., 2006; Bar Haim etal., 2006; Giampiccoloetal., 2007; Bentivoglietal., 2009; Levesque et al., 2011; Rajpurkar et al. 2016; Wang et al., 2018]

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CAS RESULTS			
CAS Step-1 (QNLI training)	73.8	N/A	N/A
CAS Step-2 (RTE training)	73.6	54.1	N/A
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Difference is statistically insignificant, hence CAS is maintaining performance sequentially

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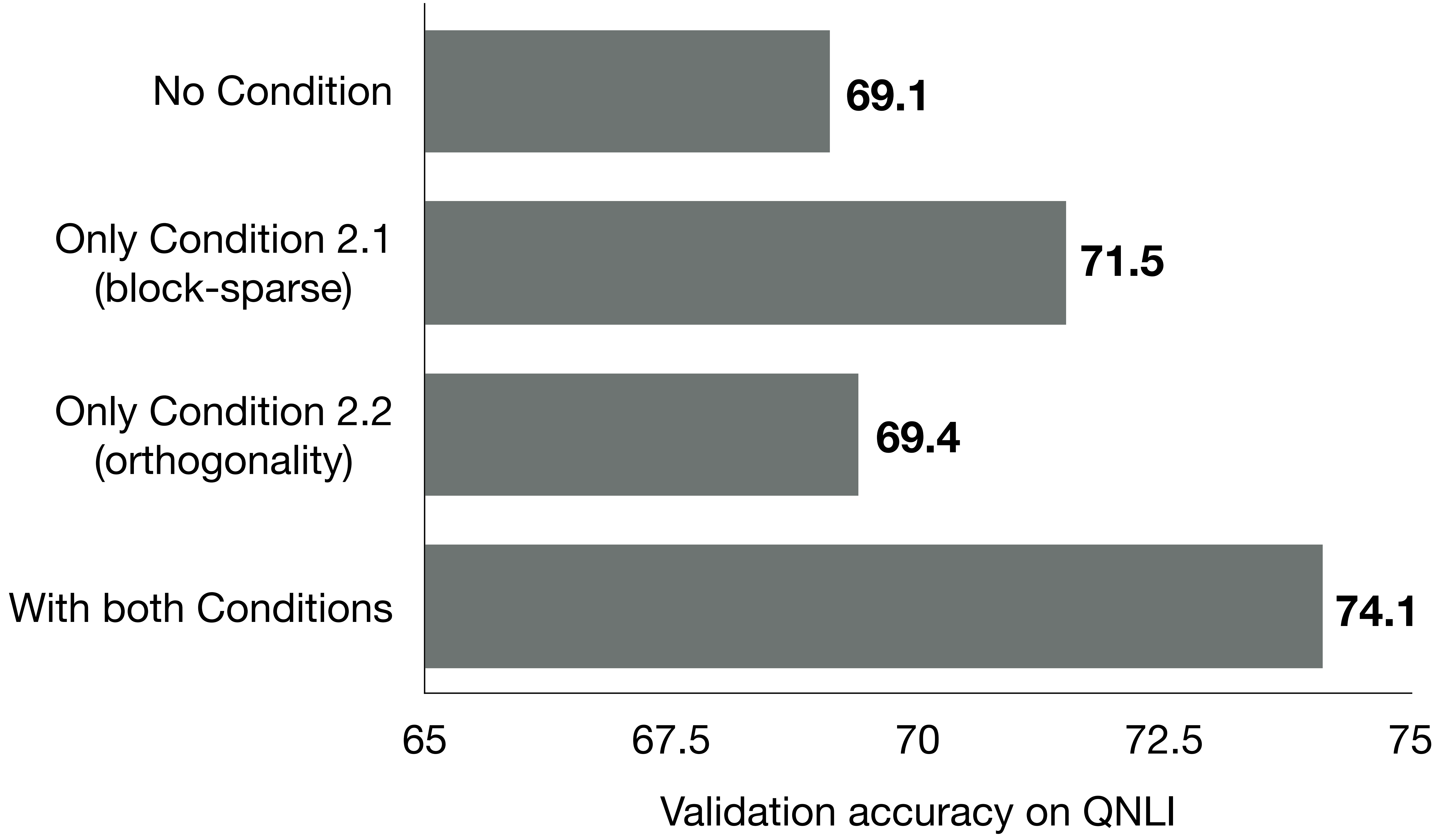

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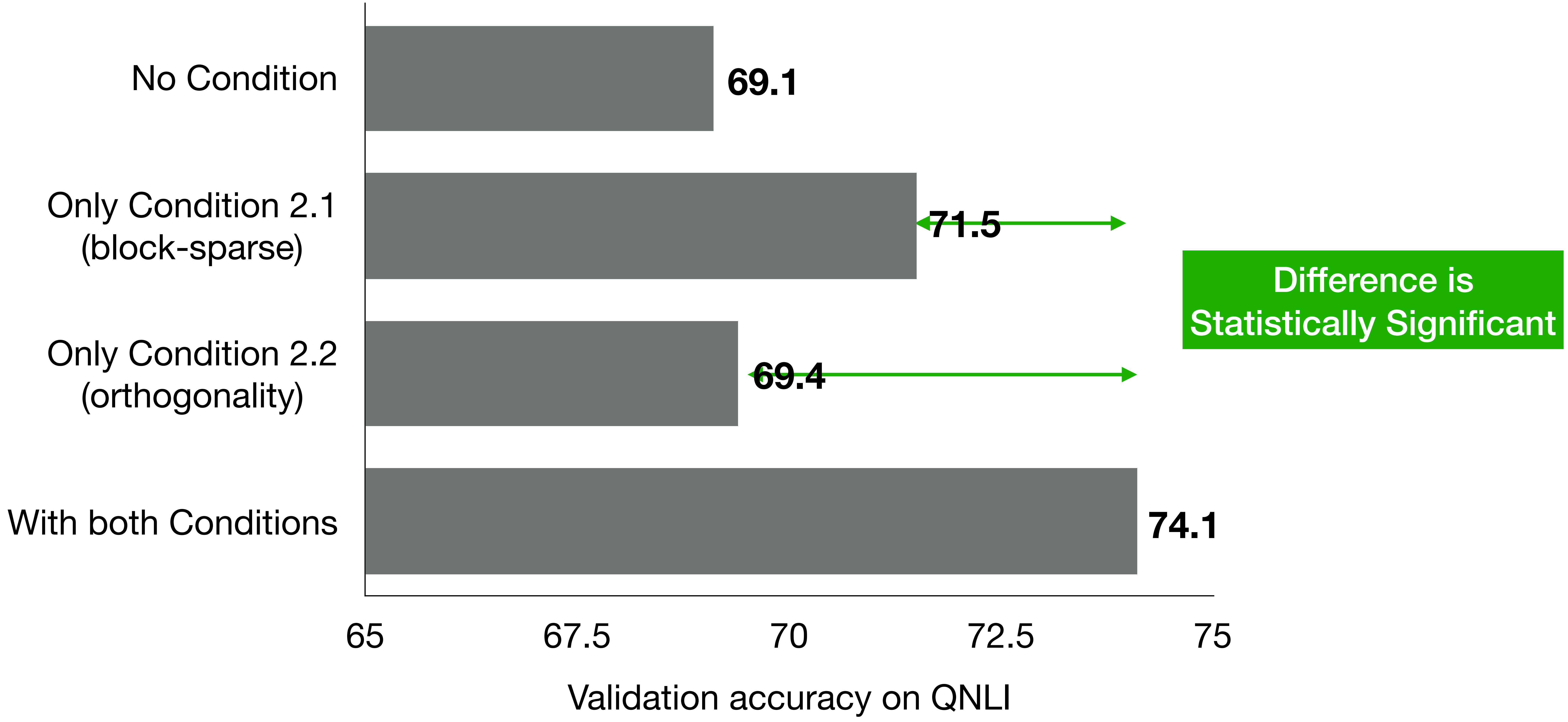

CAS Results on Video Captioning

Models	MSR-VTT					MSVD				
	C	B	R	M	AVG	C	B	R	M	AVG
Baseline (Pasunuru and Bansal, 2017b)	48.2	40.8	60.7	28.1	44.5	85.8	52.5	71.2	35.0	61.1
ENAS	48.9	41.3	61.2	28.1	44.9	87.2	52.9	71.7	35.2	61.8
CAS Step-1 (MSR-VTT training)	48.9	41.1	60.5	27.5	44.5	N/A	N/A	N/A	N/A	N/A
CAS Step-2 (MSVD training)	48.4	40.1	59.9	27.1	43.9	88.1	52.4	71.3	35.1	61.7

Table: Video captioning results with Baseline, ENAS, and CAS.

[Chen & Dolan, 2011; Xu et al., 2016]

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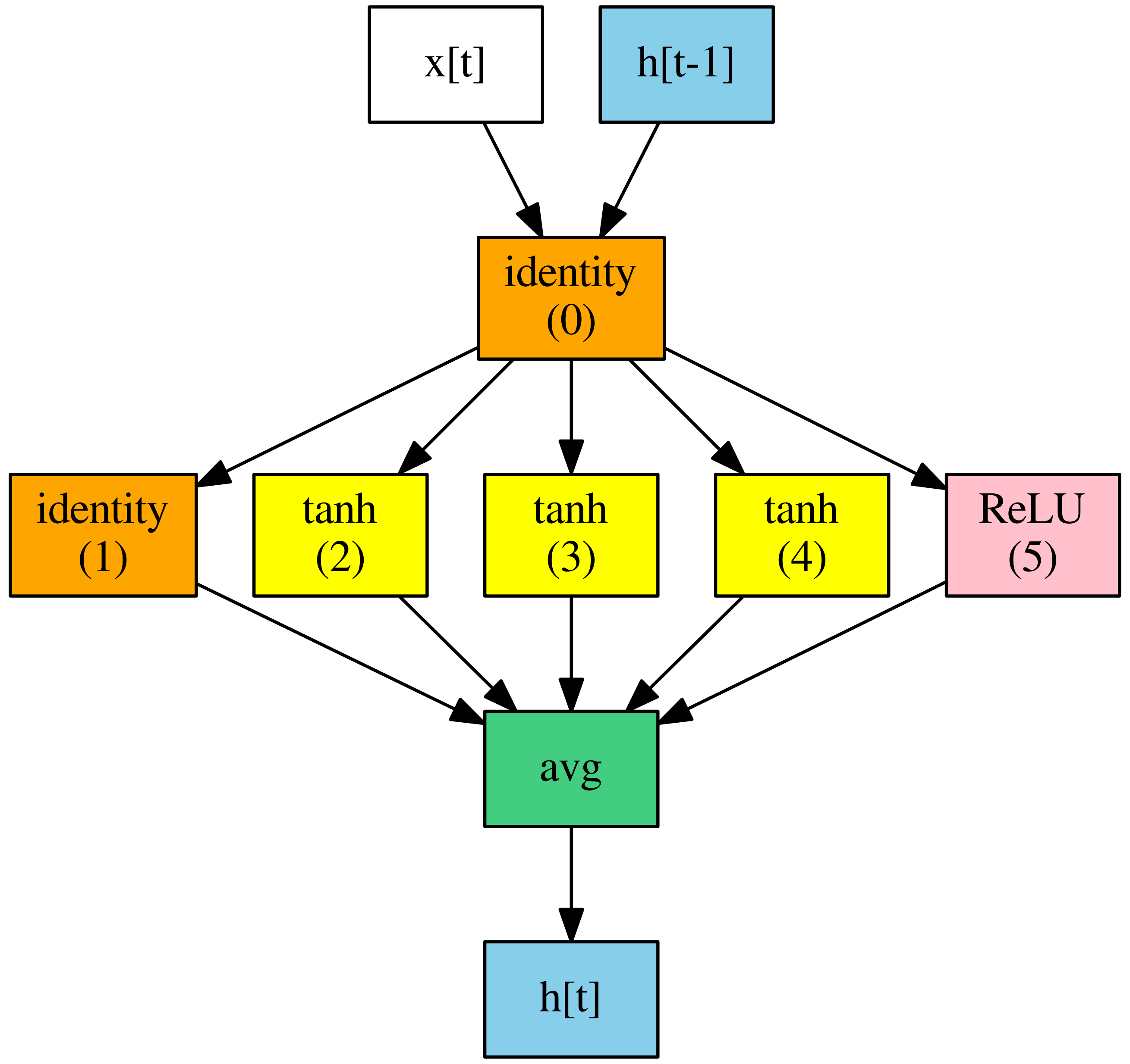
Table: Video captioning results with Baseline, ENAS, and CAS.

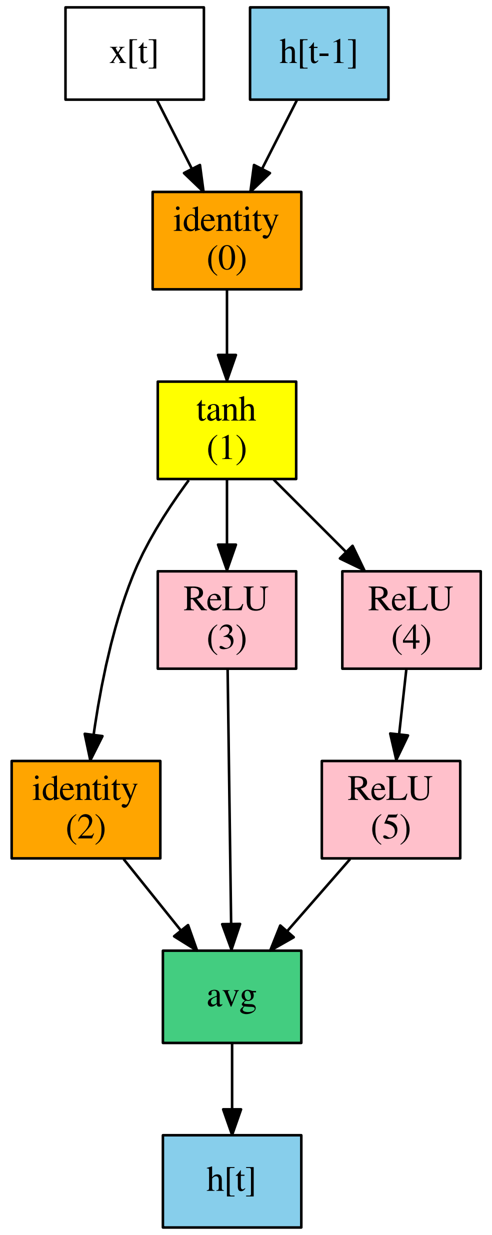
Difference is Statistically insignificant (also based on Human evaluation)
Hence CAS is maintaining performance sequentially

[Chen & Dolan, 2011; Xu et al., 2016]

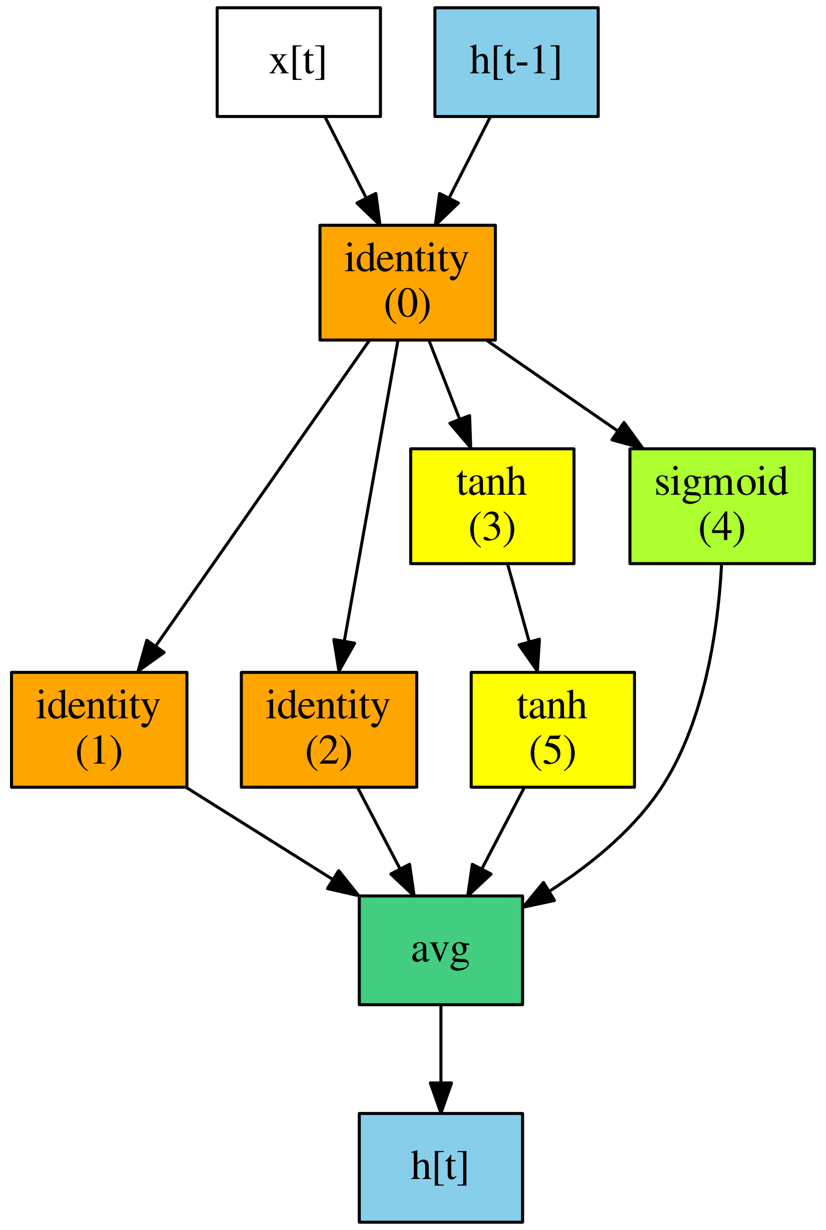
CAS Learned Cells



(a) Step-1



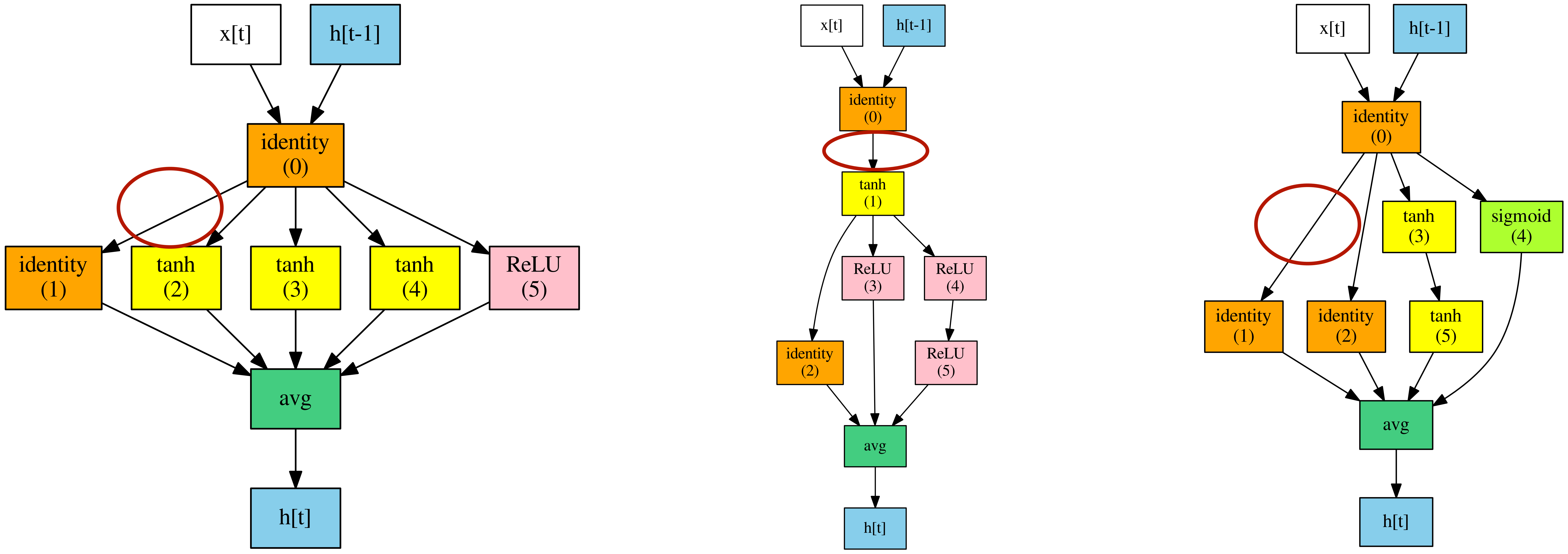
(b) Step-2



(c) Step-3

Figure: Learned cell structures for step-1, step-2, and step-3 of continual architecture search for GLUE tasks.

CAS Learned Cells



(a) Step-1 (b) Step-2 (c) Step-3

Share common edges

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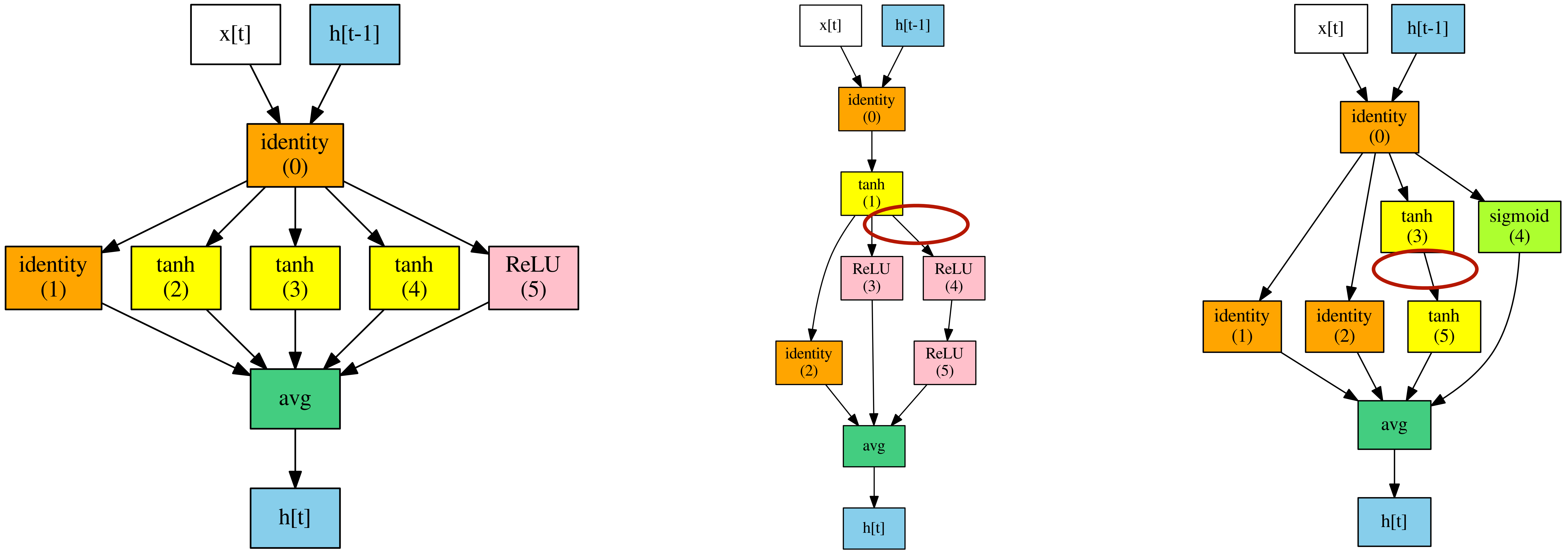
CAS Learned Cells



(a) Step-1 (b) Step-2 (c) Step-3

Task-specific new edges

Figure: Learned cell structures for step-1, step-2, and step-3 of continual architecture search for GLUE tasks.

Generalizable Cell on Multiple Tasks

- Architectures found by *NAS* are dataset dependent
- Human designed cell (e.g., *LSTM* and *GRU*) work well across multiple datasets

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Can we learn generalizable NAS cell structures?

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Multi-Task Learning!!

Multi-Task Architecture Search (MAS)

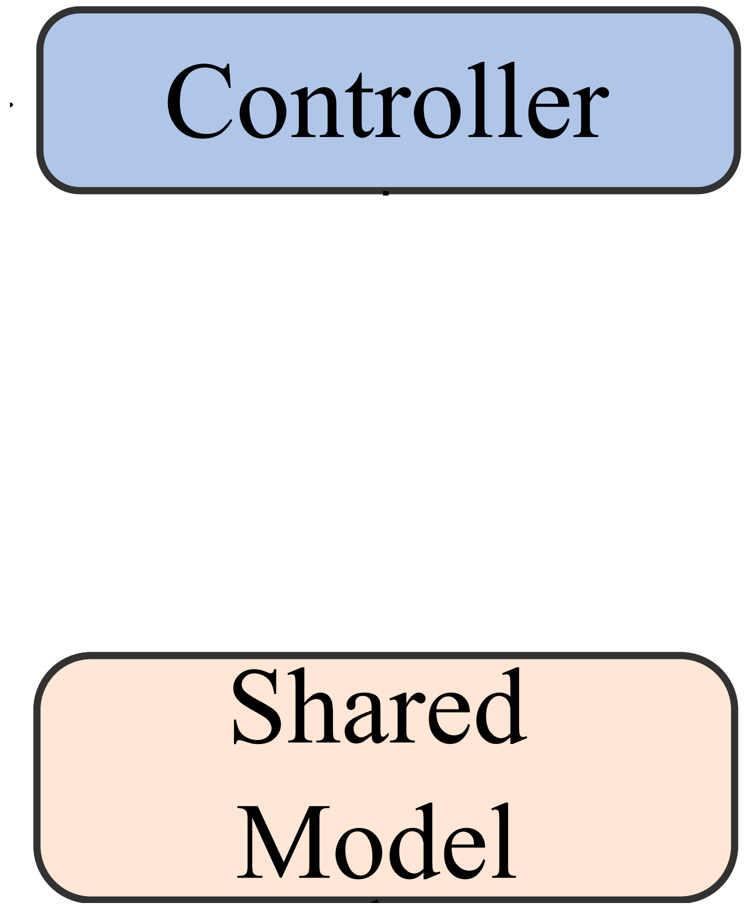
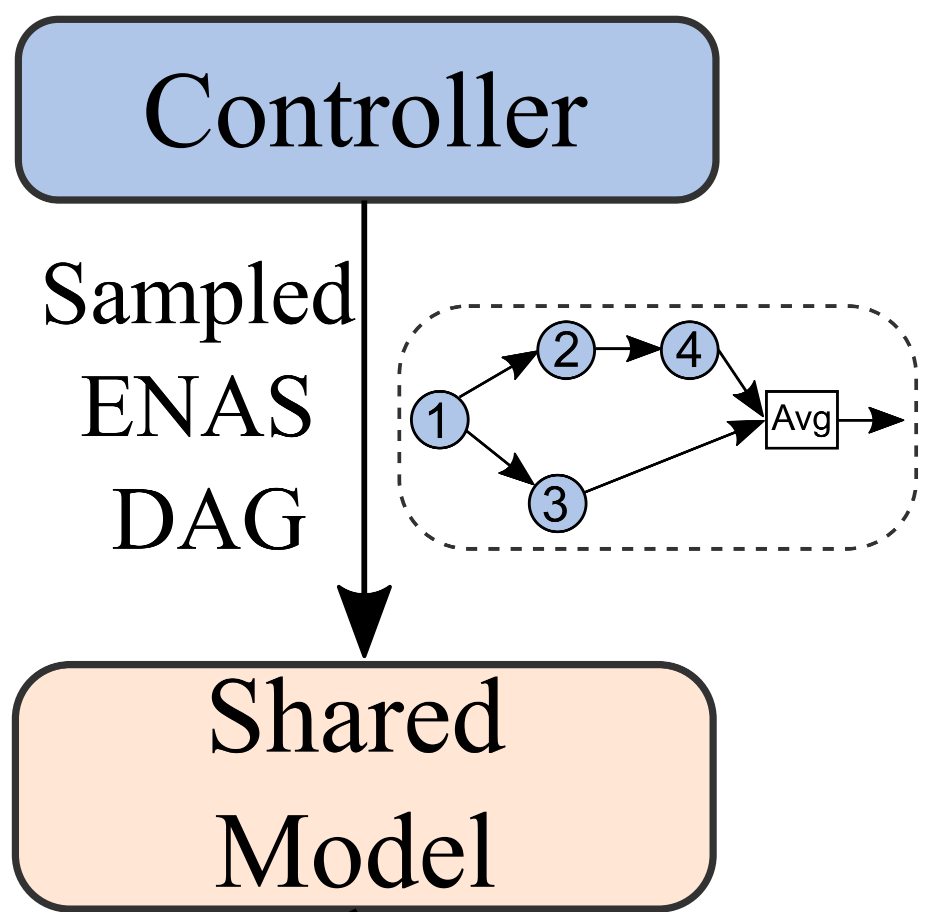


Figure: Multi-task cell structure learning using joint rewards from n datasets.

Multi-Task Architecture Search (MAS)



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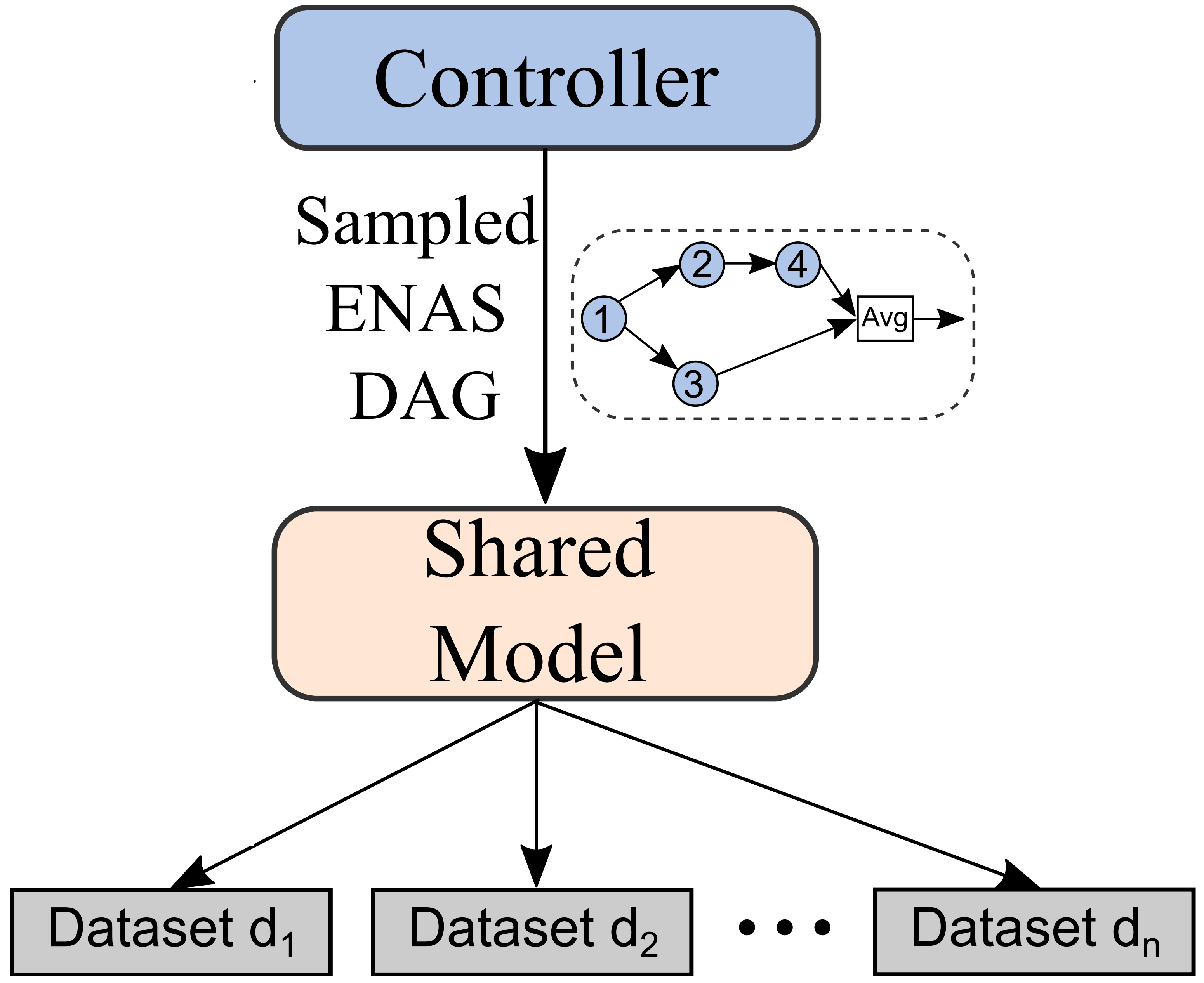

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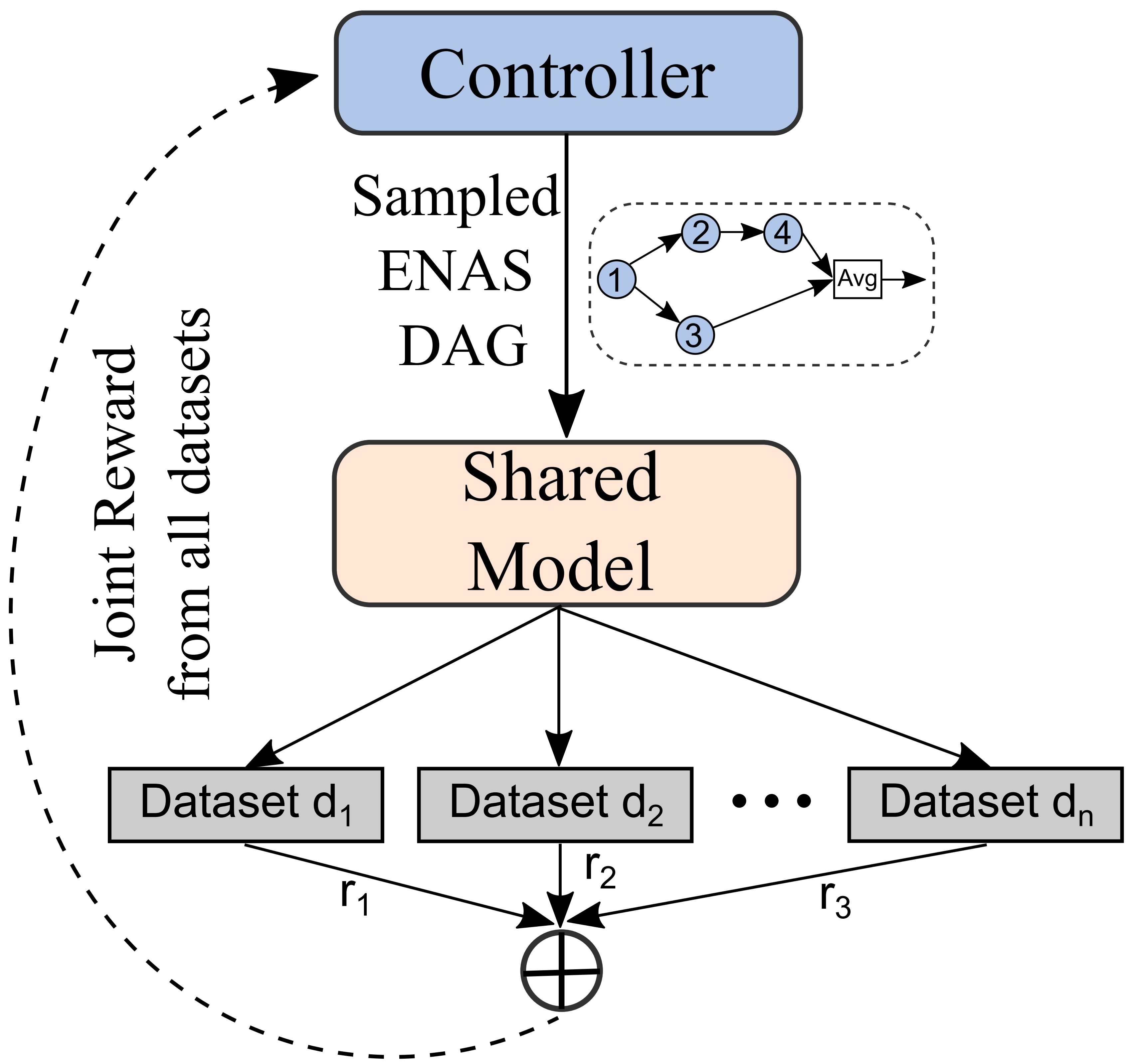

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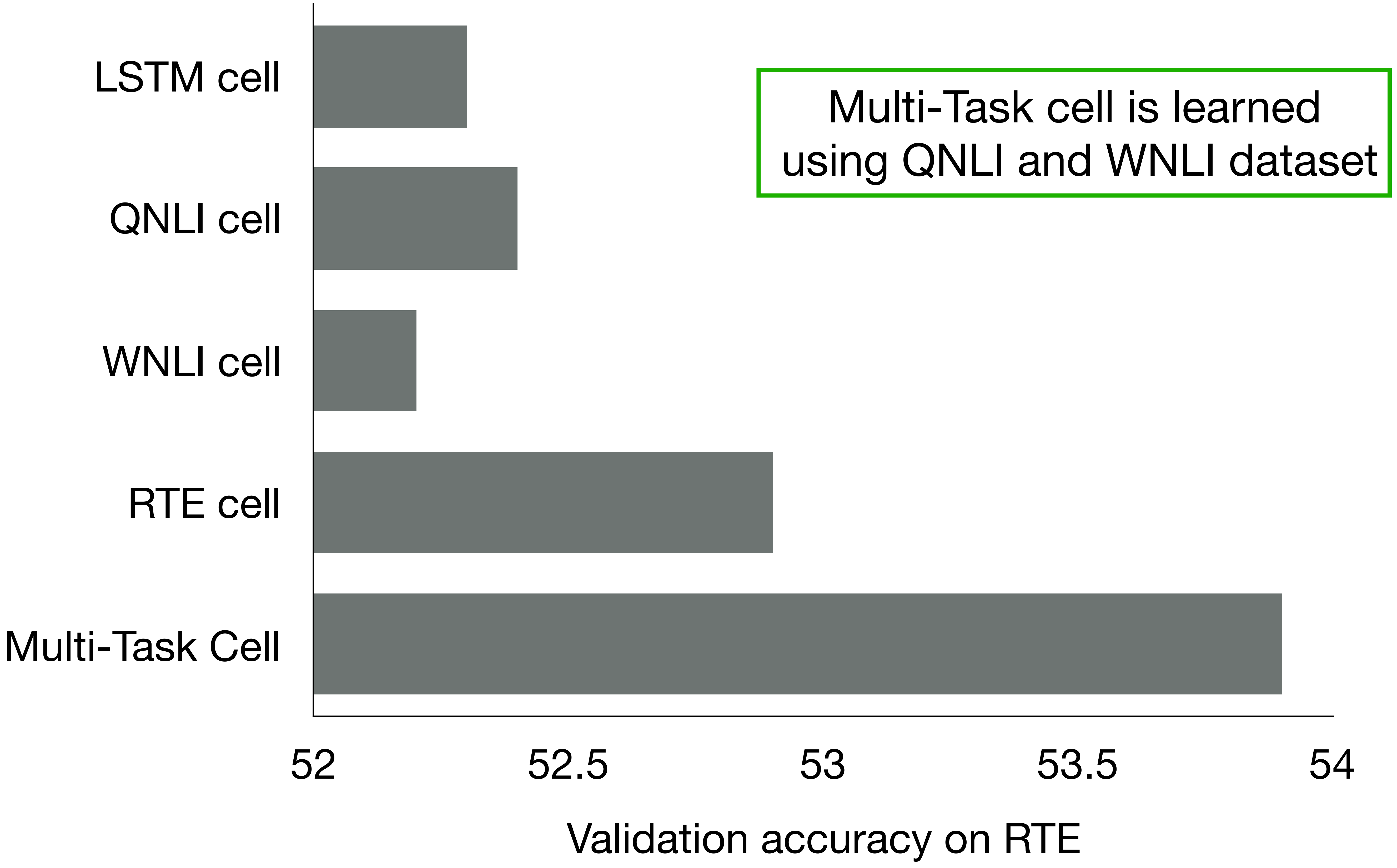
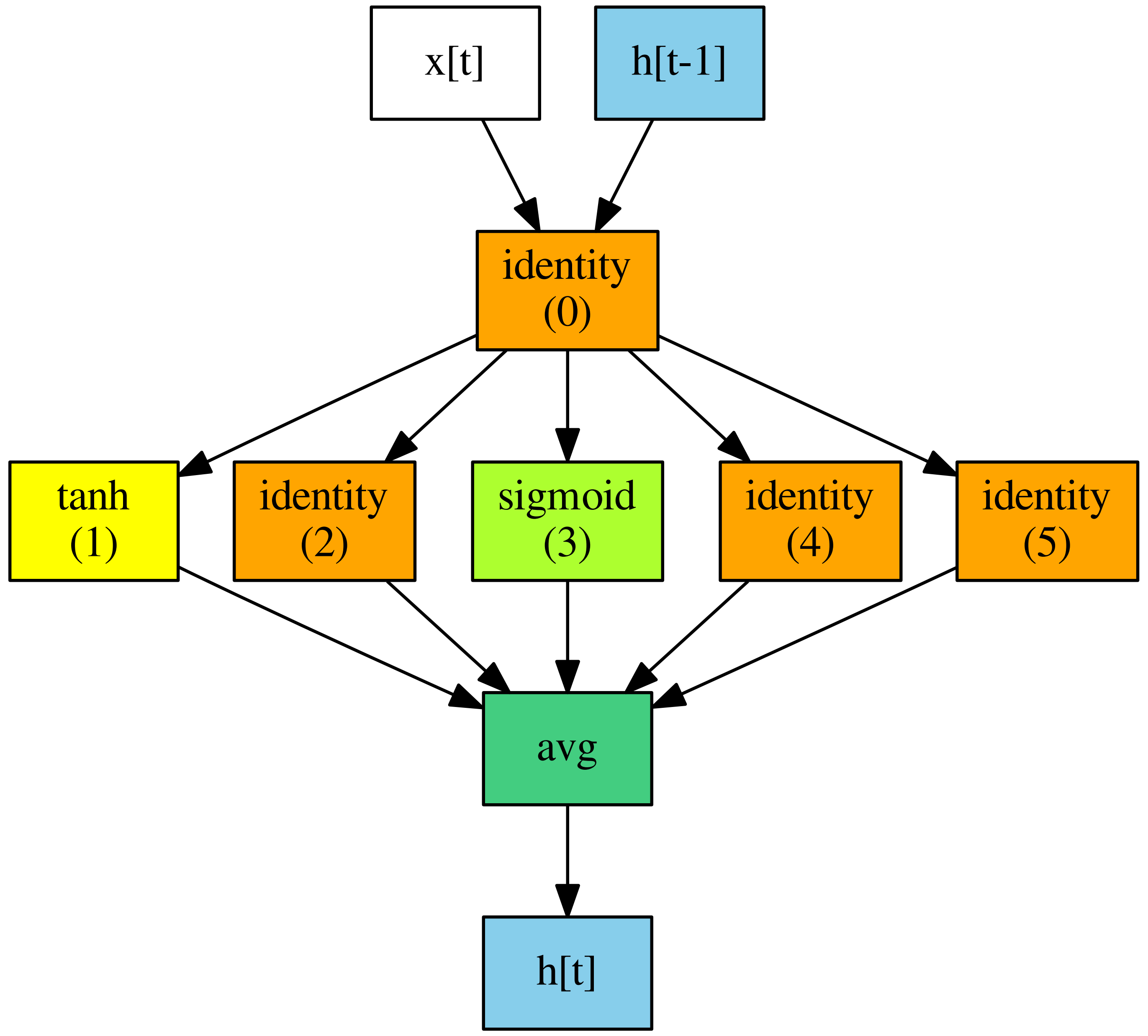
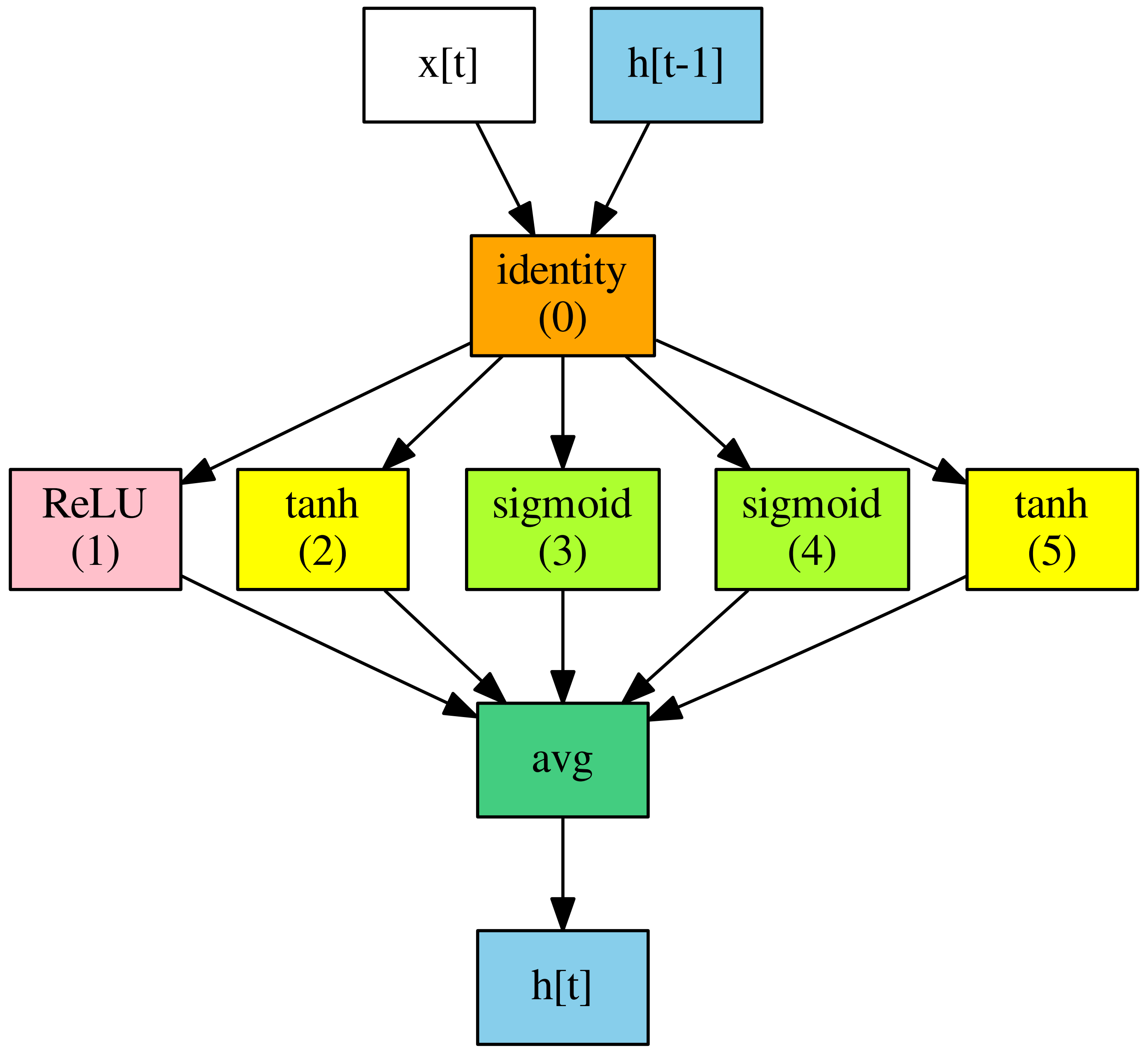
MAS Results on Text Classification



MAS Learned Cells



(a) MAS cell

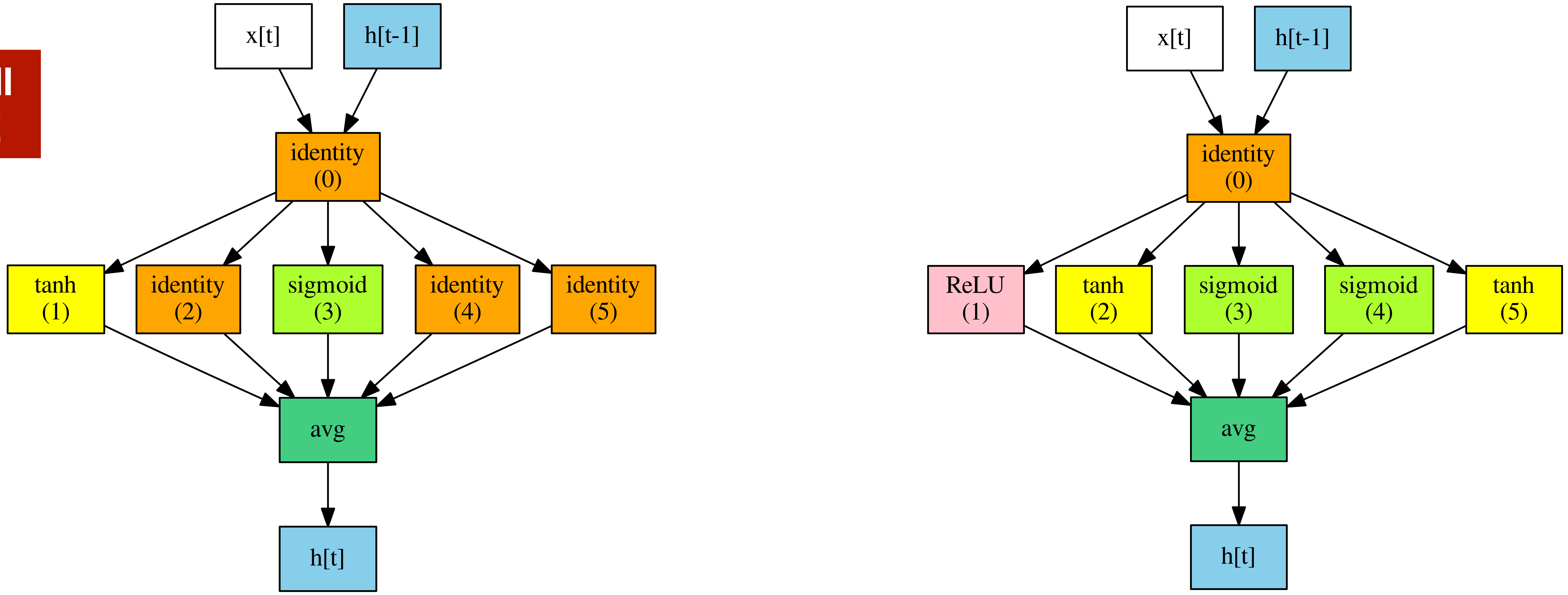


(b) RTE cell

Figure: Learned Multi-task and RTE cell Structures.

MAS Learned Cells

MAS-learned cell is less complex!



(a) MAS cell

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Thanks!

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Code: https://github.com/ramakanth-pasunuru/CAS-MAS

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