

Side-Tuning: A Baseline for Network Adaptation via Additive Side Networks



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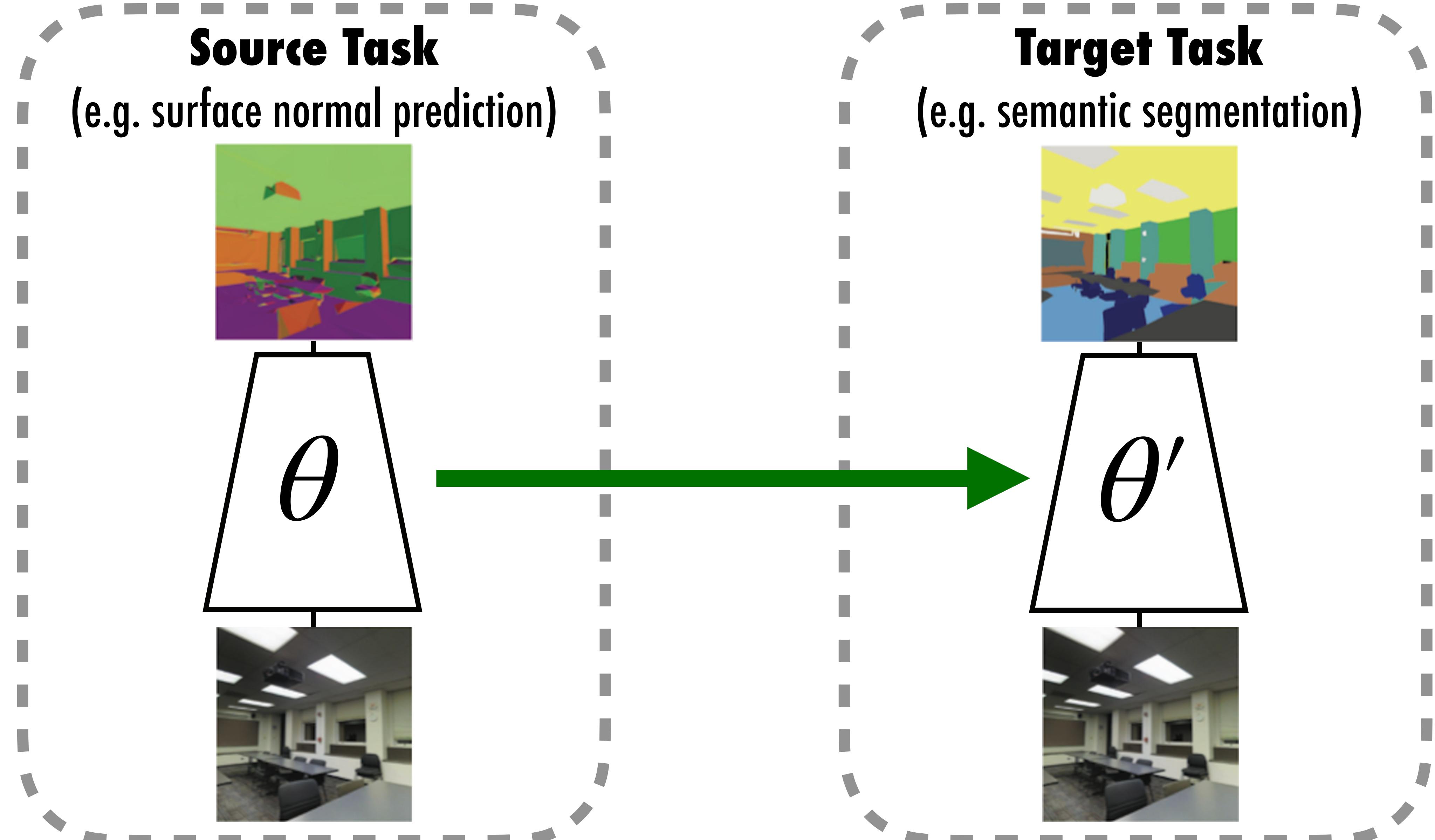


Leonidas Guibas



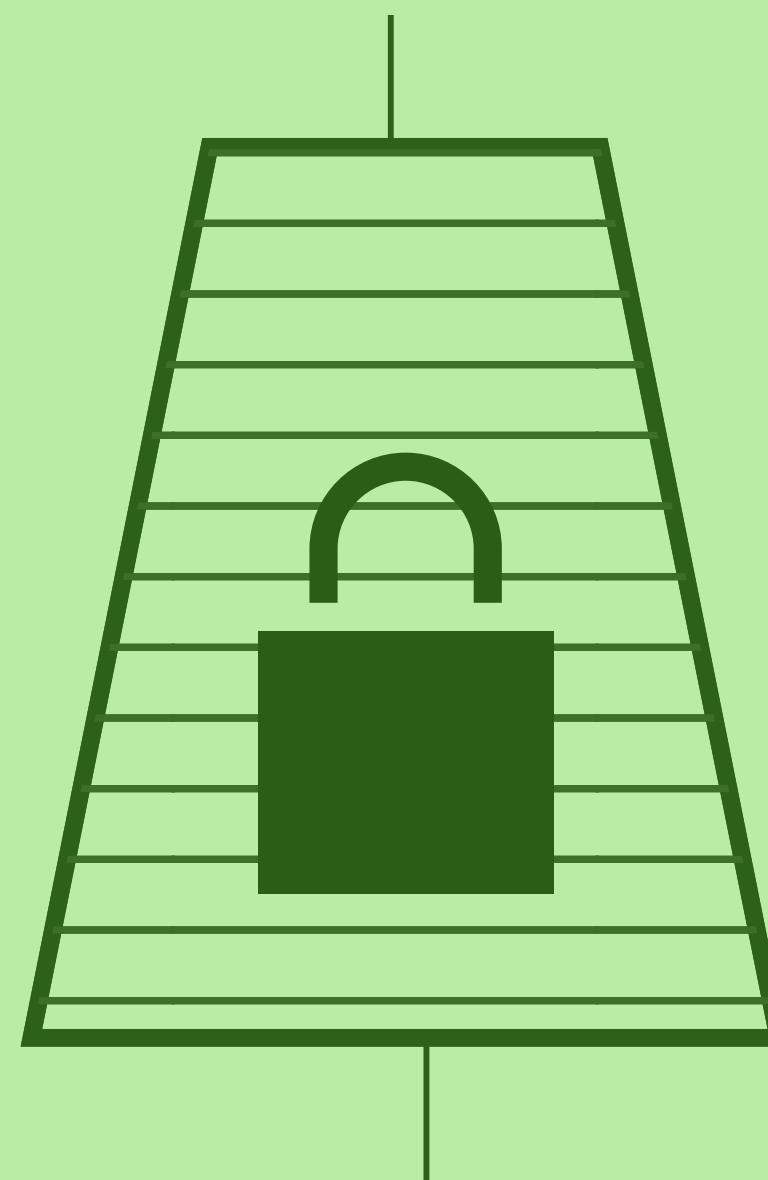
Jitendra Malik

Network Adaptation



Approaches for Network Adaptation

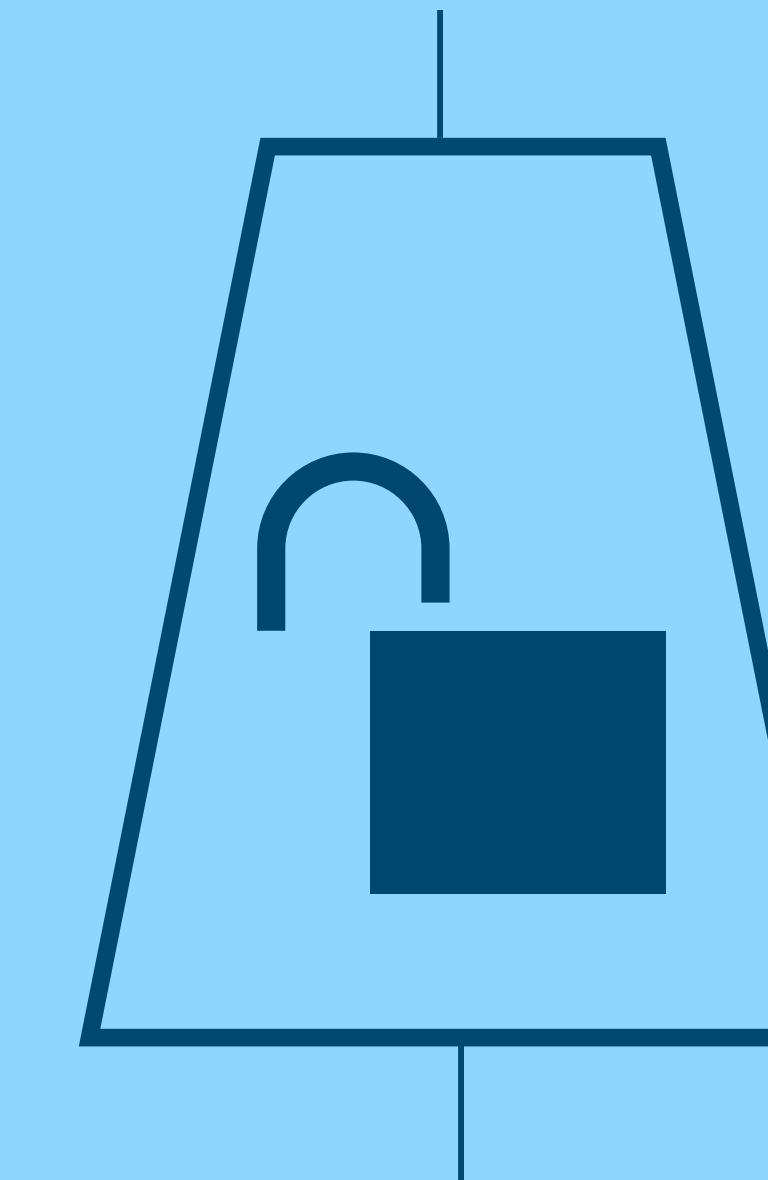
Freeze + Add



Simplest Approach:
Fixed Features

- CNN features Off the Shelf (Sharif et al.)
- Piggyback (Mallya et al.)
- PackNet (Mallya et al.)
- Deep Adaptation (Rosenfeld et al.)
- Hard Attention (Serra et al.)
- Residual Continual Learning (Lee et al.)
- Progressive NN (Rusu et al.)
- Efficient parameterization (Rebuffi et al.)

Update



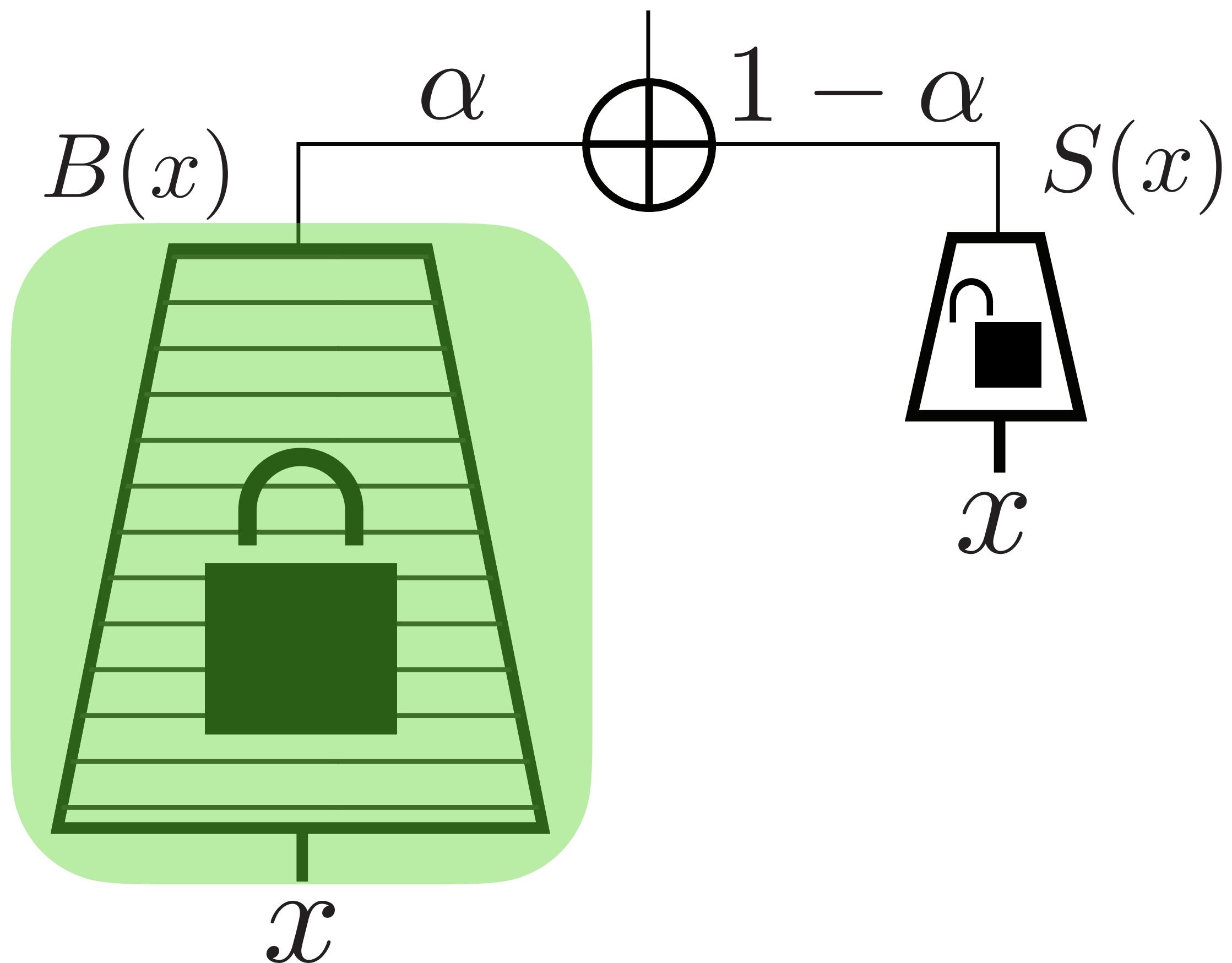
Simplest Approach:
Fine-Tuning

- Elastic Weight Consolidation (Kirkpatrick et al.)
- Learning without Forgetting (Li et al.)
- Superposition of Many Models into One (Cheung et al.)

Features vs. Fine-Tuning

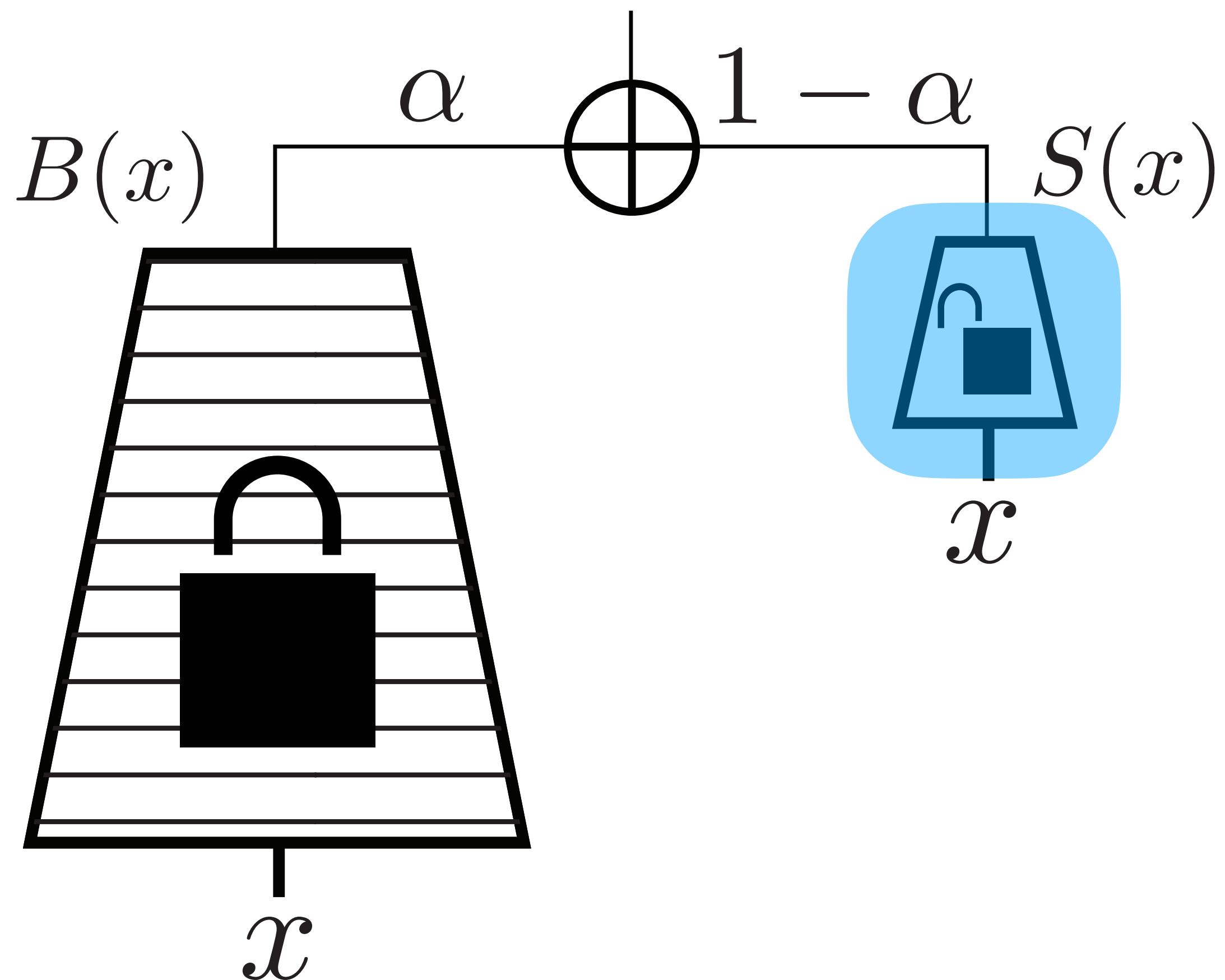
Method	1 Target Task		> 1 Target Tasks (incremental)
	Low Data	High Data	
Fixed features	✓	✗ (Info Loss)	✗ (Info Loss)
Fine-tuning	✗ (Overfit)	✓	✗ (Forgetting)

Side-tuning: a straightforward freeze+add approach



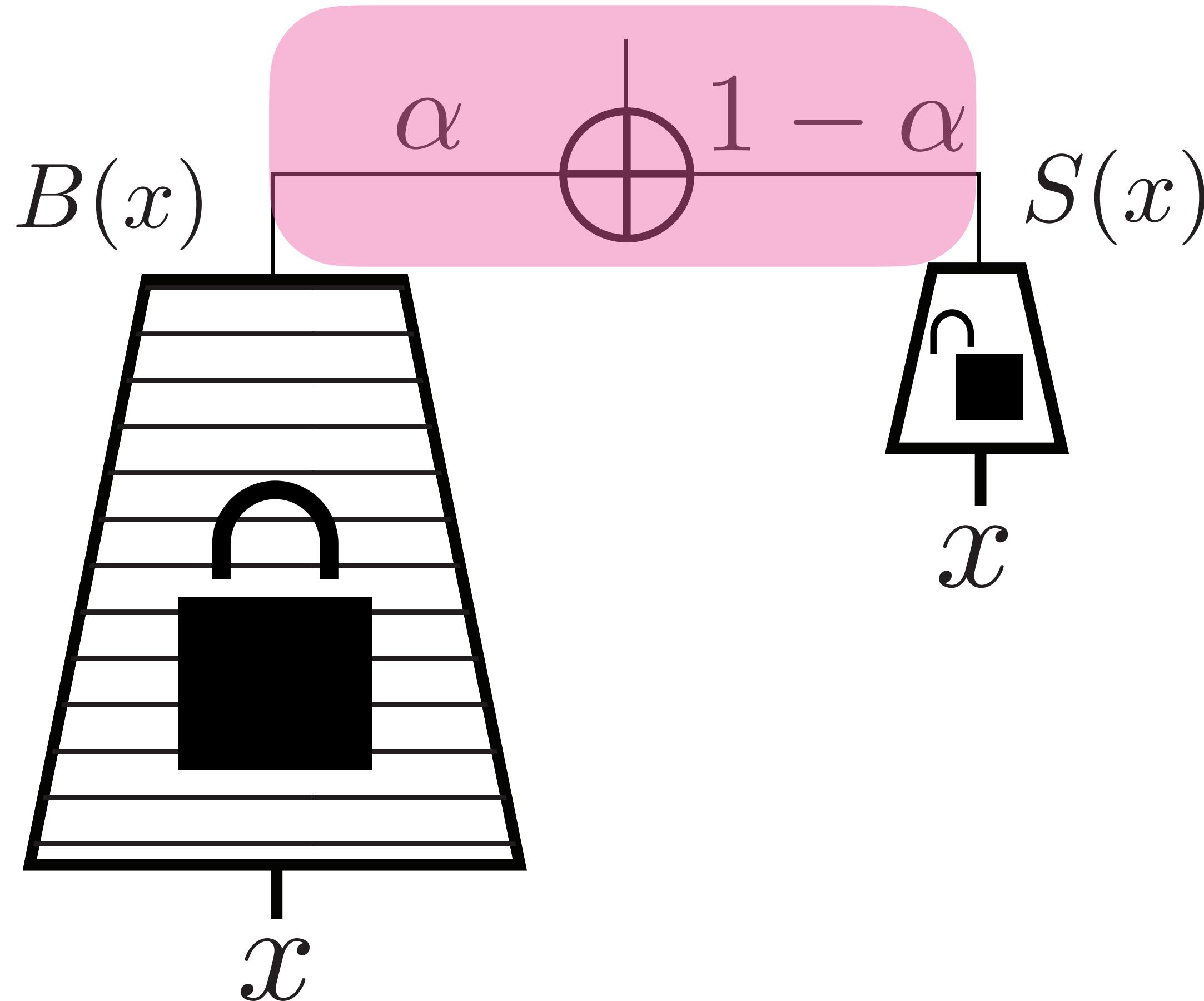
- Base network, $B(x) \rightarrow$ pre-trained

Side-tuning: a straightforward freeze+add approach



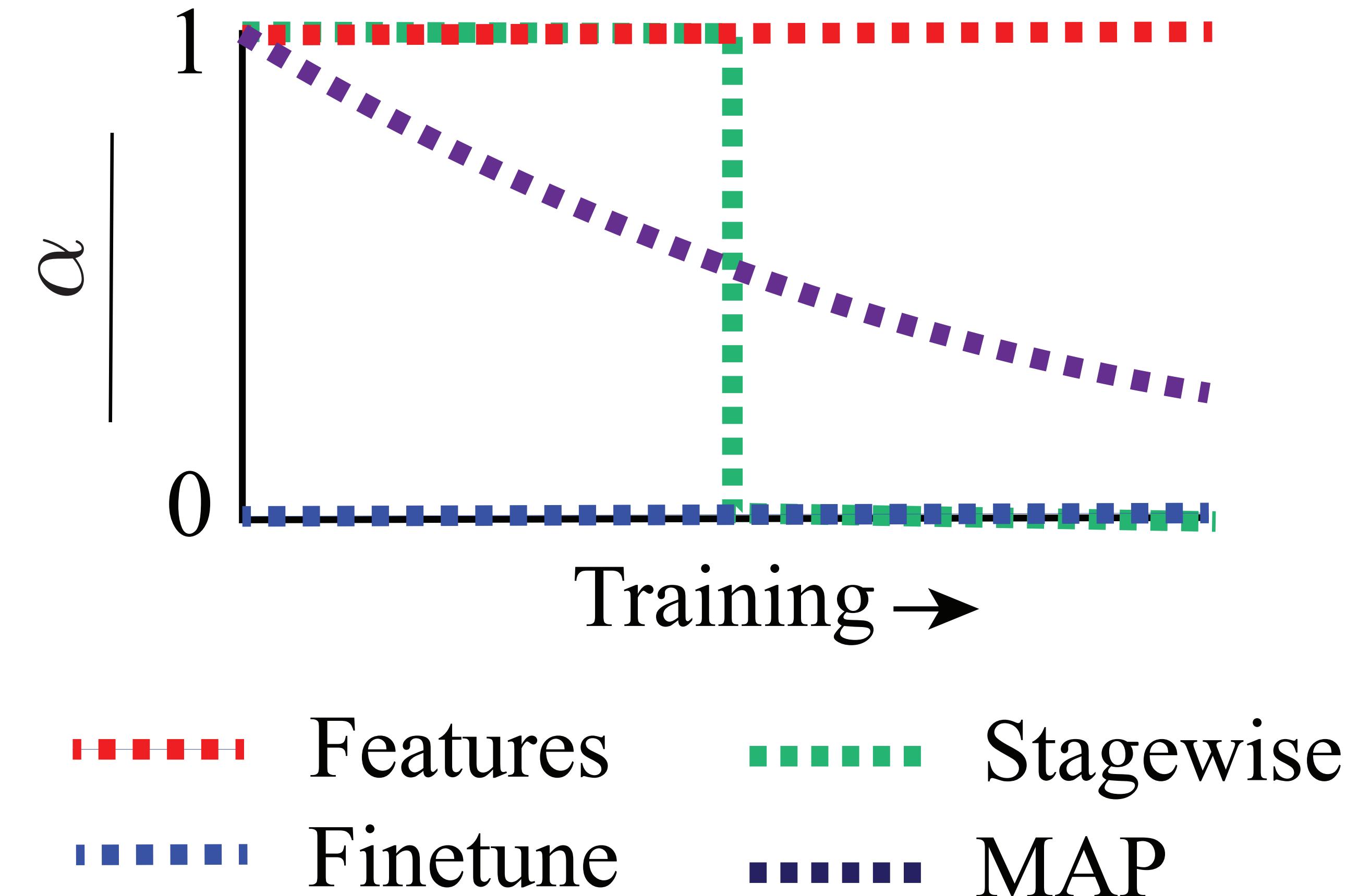
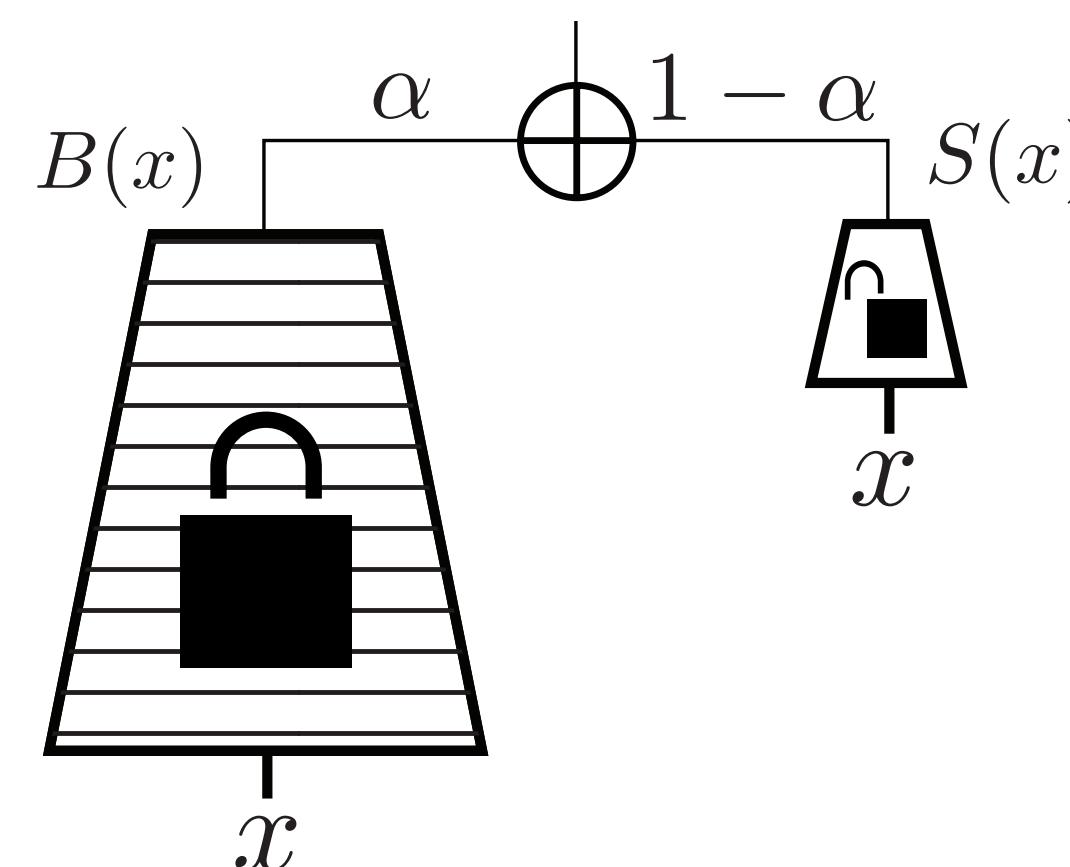
- Base network, $B(x) \rightarrow$ pre-trained
- Side network, $S(x) \rightarrow$ updated for target task

Side-tuning: a straightforward freeze+add approach

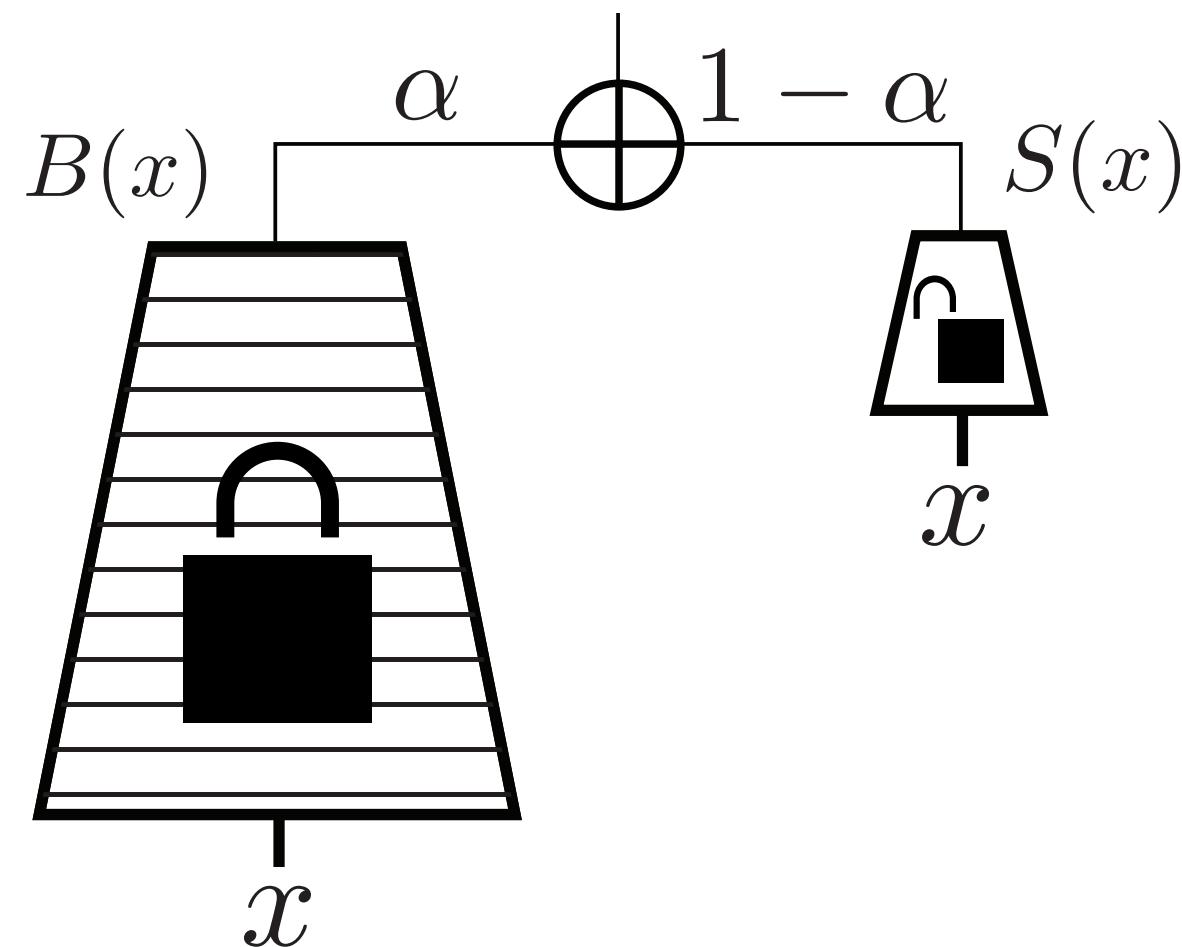


- Base network, $B(x) \rightarrow$ pre-trained
- Side network, $S(x) \rightarrow$ updated for target task
- Combined via alpha-blending

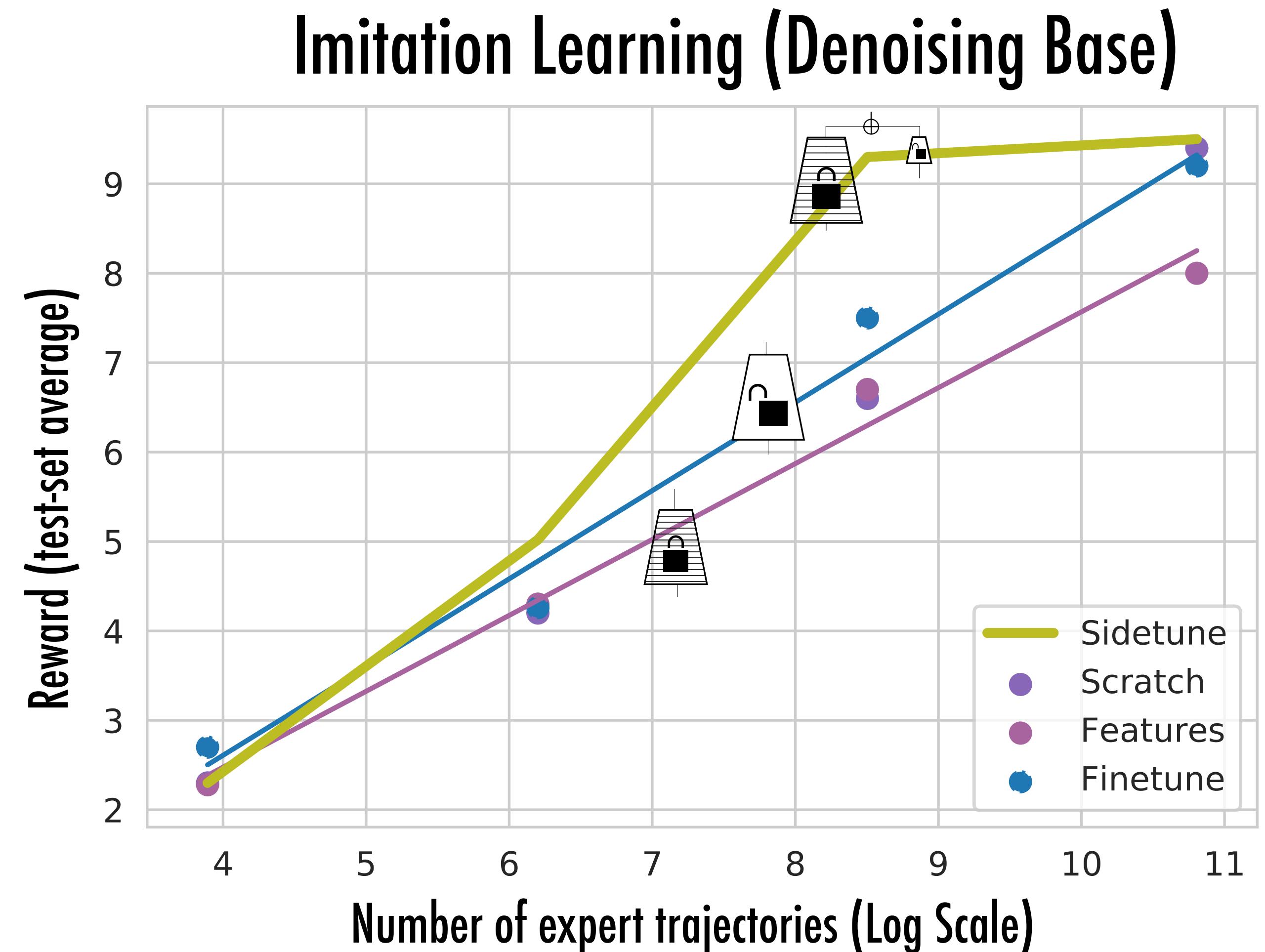
Side-Tuning: Learning α



Side-tuning for intermediate amounts of data



- Base network → useful bias
- Side network → consistency



Features vs. Fine-Tuning

Method	1 Target Task		> 1 Target Tasks (incremental)
	Low Data	High Data	
Fixed features	✓	✗ (Info Loss)	✗ (Info Loss)
Fine-tuning	✗ (Overfit)	✓	✗ (Forgetting)
<i>Side-tuning</i>	✓	✓	✓

Side-tuning in varied settings

Computer Vision

Query Image

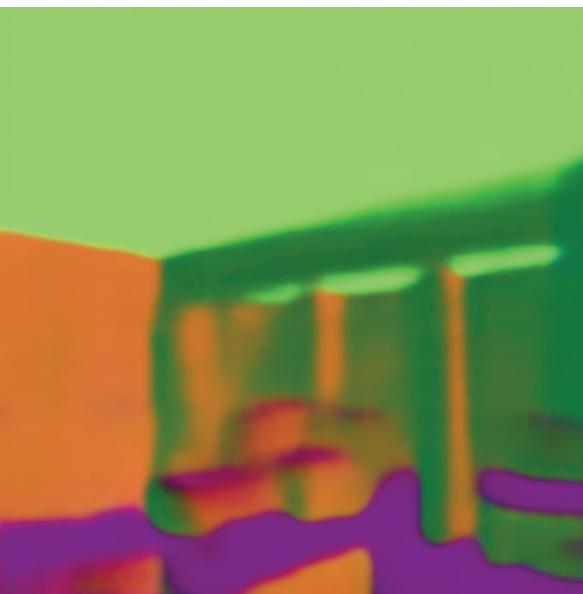


3D Curvature



Taskonomy (Zamir et al.)

Surface Normals



Object Class.

Top 5 prediction:

- sliding door
- home theater, home theatre
- studio couch, day bed
- china cabinet, china closet
- entertainment center

NLP

Article: Endangered Species Act

Paragraph: “...Other legislation followed, including the Migratory Bird Conservation Act of 1929, a **1937 treaty** prohibiting the hunting of right and gray whales, and the **Bald Eagle Protection Act of 1940**. These **later laws** had a low cost to society—the species were relatively rare—and little **opposition** was raised.”

Question 1: “Which laws faced significant **opposition**? ”

Plausible Answer: **later laws**

Question 2: “What was the name of the **1937 treaty**? ”

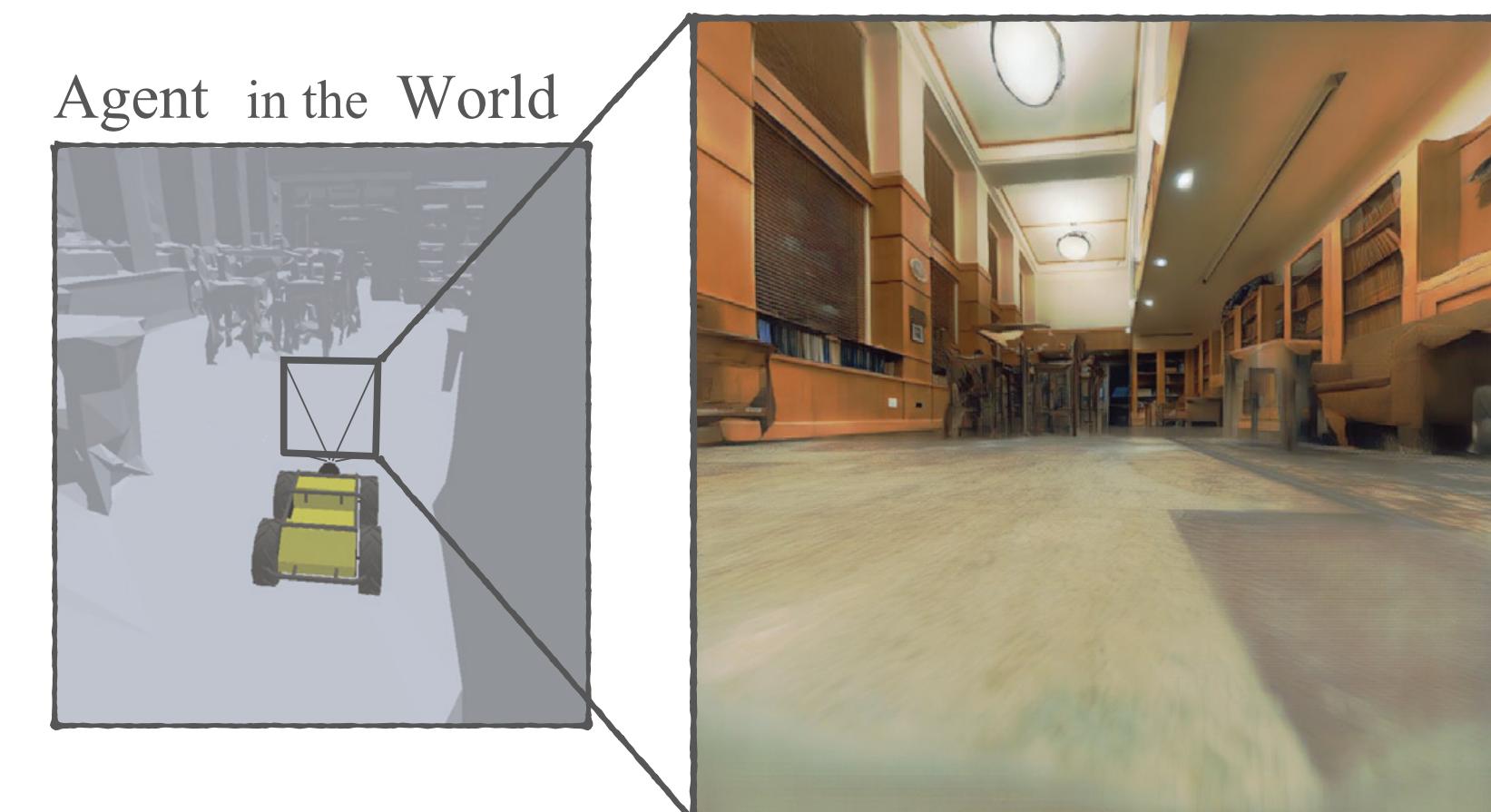
Plausible Answer: **Bald Eagle Protection Act**

SQuAD v2 (Rajpurkar et al.)

Robotics (Tested in Gibson)

Visual Observation

Agent in the World



Habitat (Savva et al.)
Gibson (Xia et al.)

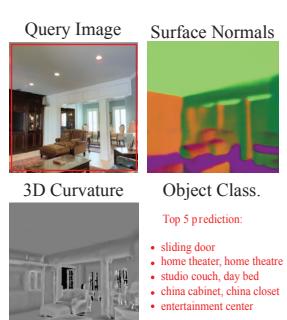
Solid performance across multiple domains and settings

Solid performance across multiple domains and settings

Transfer Learning in Taskonomy

Method	From Curvature (100/4M ims.)	
	Normals (MSE ↓)	Obj. Cls. (Acc. ↑)
Fine-tune	0.200 / 0.094	24.6 / 62.8
Features	0.204 / 0.117	24.4 / 45.4
Scratch	0.323 / 0.095	19.1 / 62.3
<i>Side-tune</i>	0.199 / 0.095	24.8 / 63.3

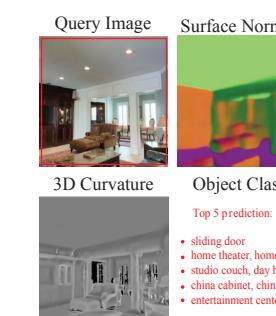
- Low-dimensional prediction tasks
- High-dimensional pix-to-pix tasks
- Low-data (100 images)
- High-data (4M images)



Solid performance across multiple domains and settings

	Transfer Learning in Taskonomy		QA on SQuAD	
Method	From Curvature (100/4M ims.)		Match (\uparrow)	
	Normals (MSE \downarrow)	Obj. Cls. (Acc. \uparrow)	Exact	F1
Fine-tune	0.200 / 0.094	24.6 / 62.8	79.0	82.2
Features	0.204 / 0.117	24.4 / 45.4	49.4	49.5
Scratch	0.323 / 0.095	19.1 / 62.3	0.98	4.65
<i>Side-tune</i>	0.199 / 0.095	24.8 / 63.3	79.6	82.7

- Low-dimensional prediction tasks
 - High-dimensional pix-to-pix tasks
 - Low-data (100 images)
 - High-data (4M images)
- NLP domain
 - Different architecture (transformer)

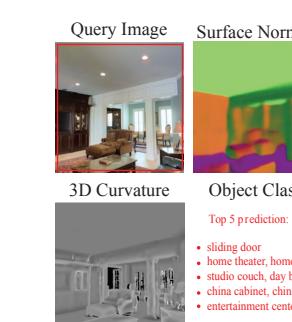


Article: Endangered Species Act
Paragraph: "...Other legislation followed, including the Migratory Bird Conservation Act of 1929, a 1937 treaty prohibiting the hunting of right and gray whales, and the Bald Eagle Protection Act of 1940. These later laws had a low cost to society—the species were relatively rare—and little opposition was raised."
Question 1: "Which laws faced significant opposition?"
Plausible Answer: later laws
Question 2: "What was the name of the 1937 treaty?"
Plausible Answer: Bald Eagle Protection Act

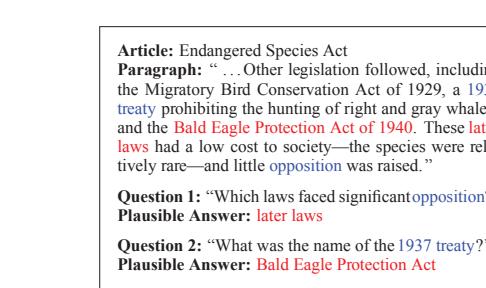
Solid performance across multiple domains and settings

	Transfer Learning in Taskonomy		QA on SQuAD		Navigation (IL)	
Method	From Curvature (100/4M ims.)		Match (\uparrow)			Nav. Rew. (\uparrow)
	Normals (MSE \downarrow)	Obj. Cls. (Acc. \uparrow)	Exact	F1	Curv.	Denoise
Fine-tune	0.200 / 0.094	24.6 / 62.8	79.0	82.2	10.5	9.2
Features	0.204 / 0.117	24.4 / 45.4	49.4	49.5	11.2	8.2
Scratch	0.323 / 0.095	19.1 / 62.3	0.98	4.65	9.4	9.4
<i>Side-tune</i>	0.199 / 0.095	24.8 / 63.3	79.6	82.7	11.1	9.5

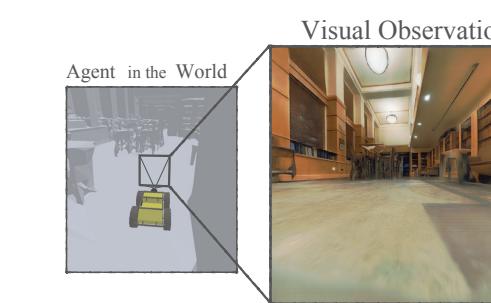
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- NLP domain
- Different architecture (transformer)



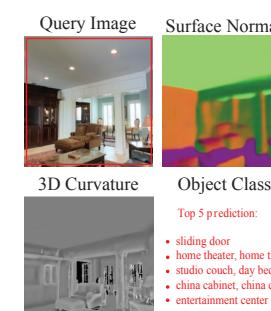
- Active POMDP settings



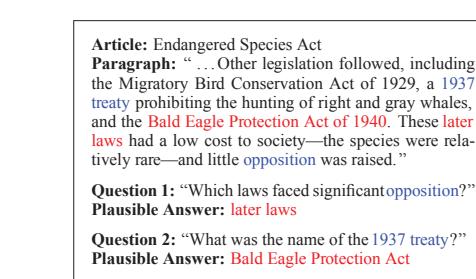
Solid performance across multiple domains and settings

Transfer Learning in Taskonomy		QA on SQuAD		Navigation (IL)		Navigation (RL)		
From Curvature (100/4M ims.)		Match (\uparrow)		Nav. Rew. (\uparrow)		Nav. Rew. (\uparrow)		
Method	Normals (MSE \downarrow) Obj. Cls. (Acc. \uparrow)	Exact F1	Curv. Denoise	Curv. Denoise				
Fine-tune	0.200 / 0.094	24.6 / 62.8	79.0	82.2	10.5	9.2	10.7	10.0
Features	0.204 / 0.117	24.4 / 45.4	49.4	49.5	11.2	8.2	11.9	8.3
Scratch	0.323 / 0.095	19.1 / 62.3	0.98	4.65	9.4	9.4	7.5	7.5
<i>Side-tune</i>	0.199 / 0.095	24.8 / 63.3	79.6	82.7	11.1	9.5	11.8	10.4

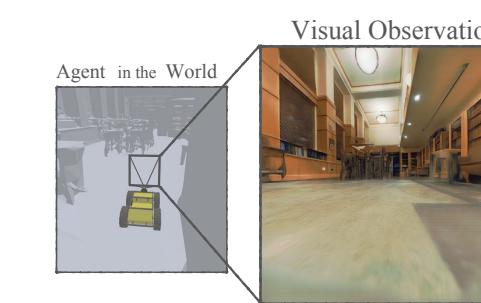
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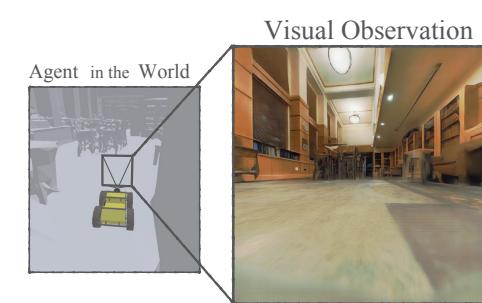
- NLP domain
- Different architecture (transformer)



- Active POMDP settings



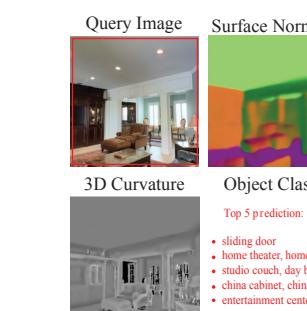
- Different learning algorithms (PPO instead of supervised learning)



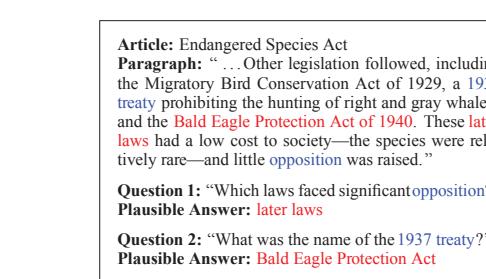
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Transfer Learning in Taskonomy			QA on SQuAD		Navigation (IL)		Navigation (RL)		
Method	From Curvature (100/4M ims.)		Match (\uparrow)	Nav. Rew. (\uparrow)		Nav. Rew. (\uparrow)		Nav. Rew. (\uparrow)	
	Normals (MSE \downarrow)	Obj. Cls. (Acc. \uparrow)	Exact	F1	Curv.	Denoise	Curv.	Denoise	
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Scratch	0.323 / 0.095	19.1 / 62.3	0.98	4.65	9.4	9.4	7.5	7.5	
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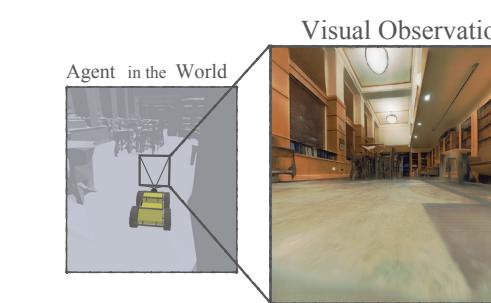
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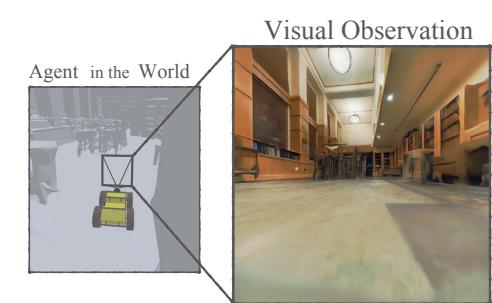
- NLP domain
- Different architecture (transformer)



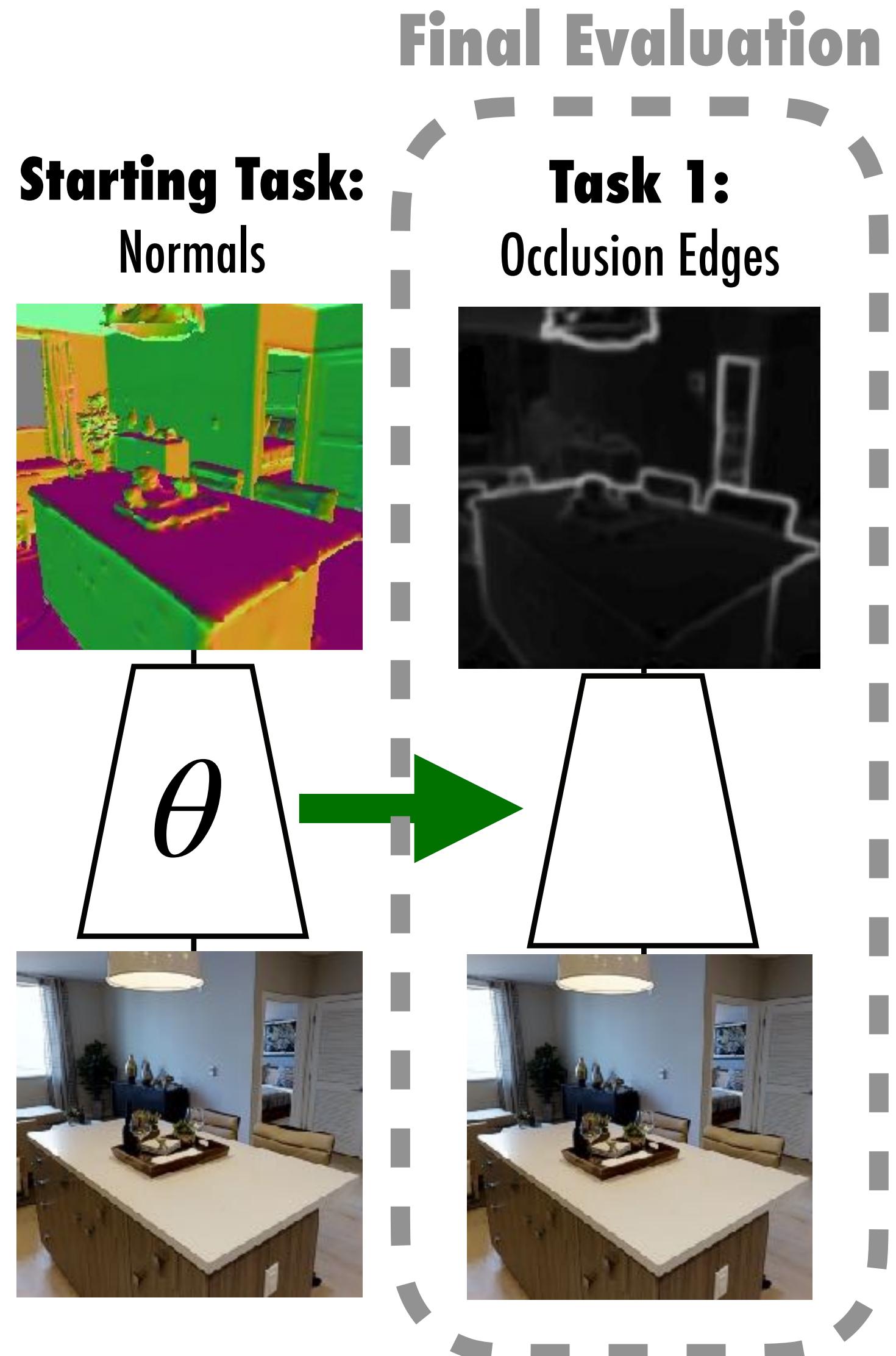
- Active POMDP settings



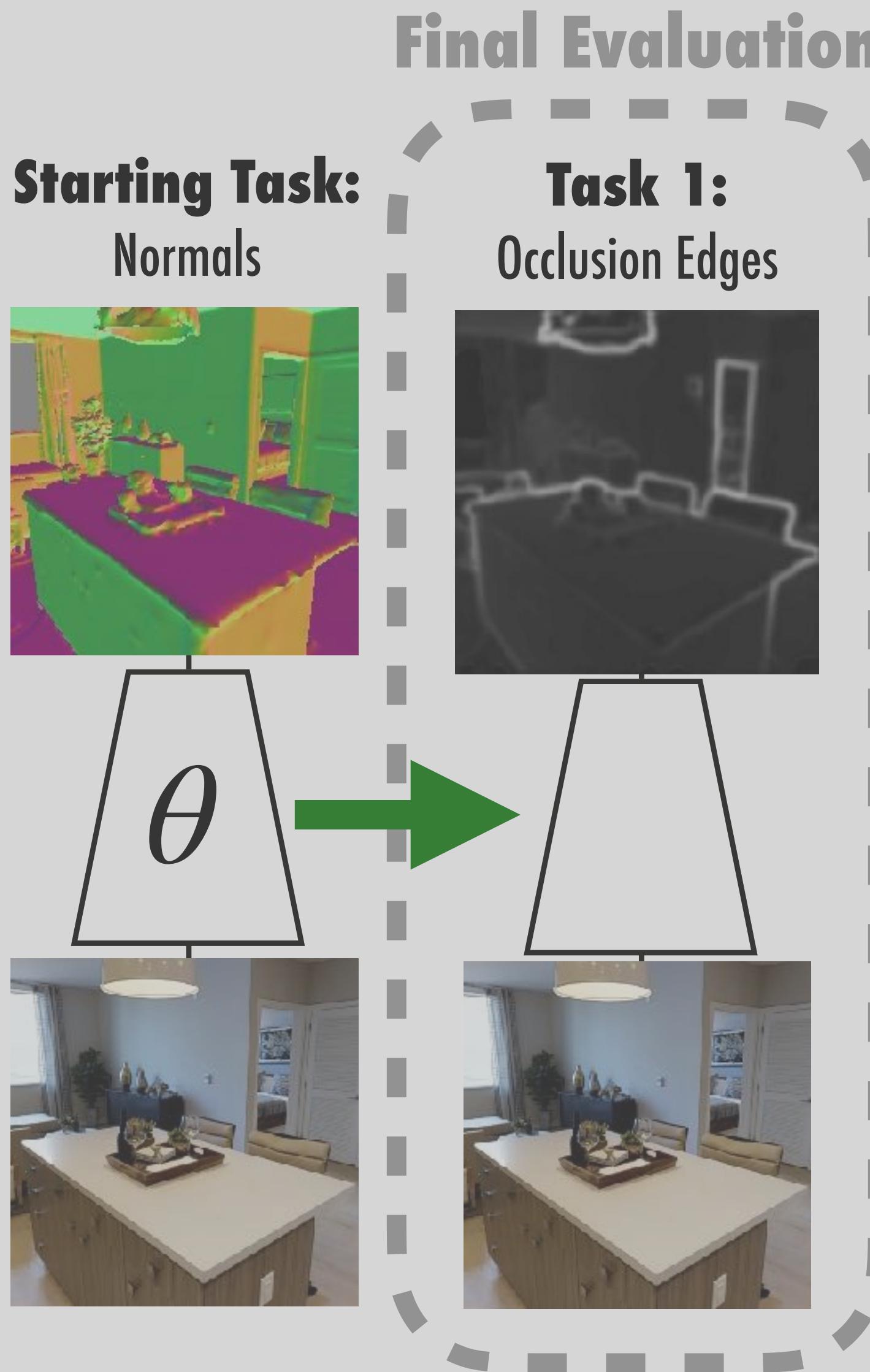
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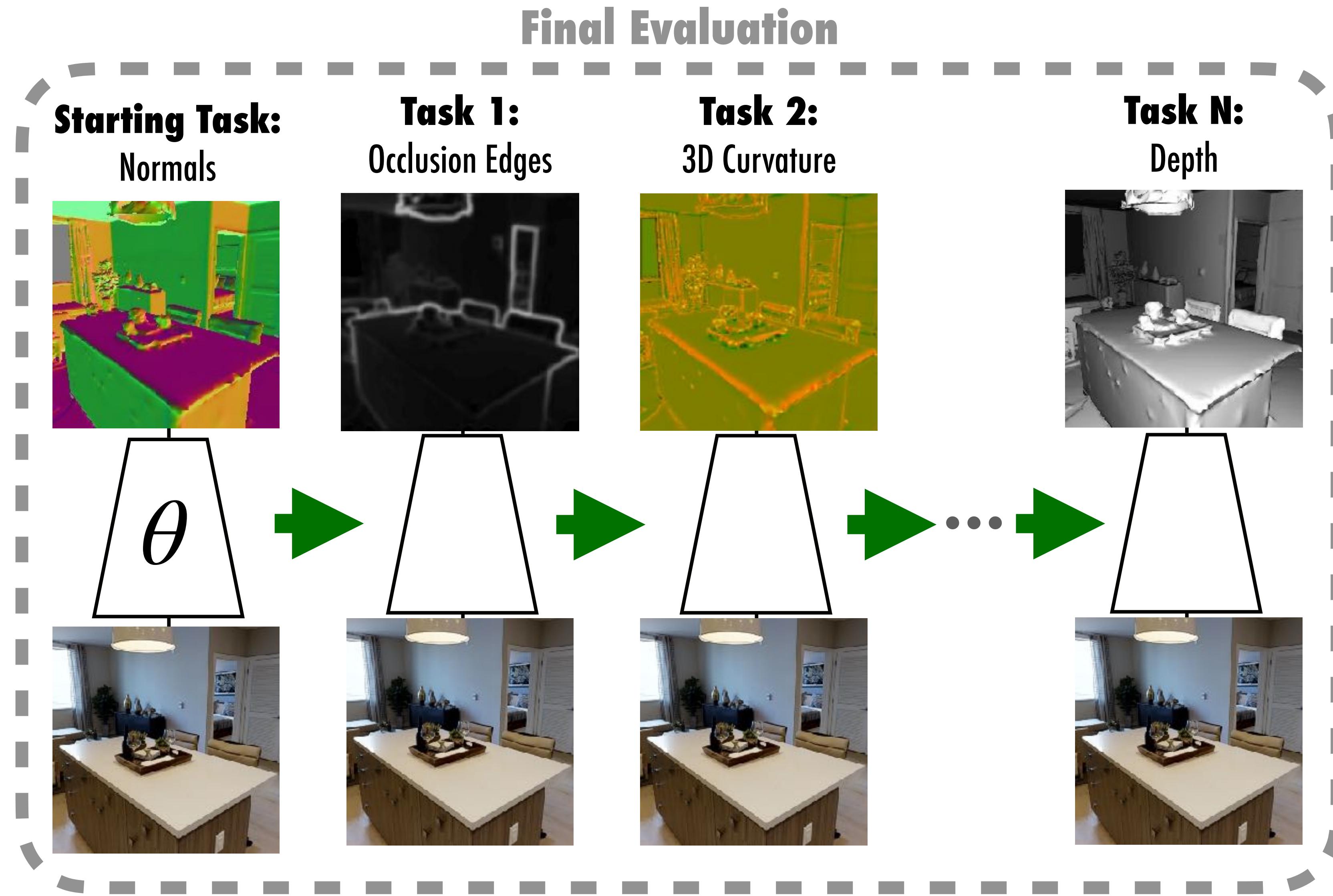
Adaptation



Adaptation



Incremental Learning



Incremental learning: forgetting and rigidity

Catastrophic Forgetting

Tendency of a network to lose previously learned knowledge upon learning new information.

Catastrophic interference in connectionist networks: the sequential learning problem (McCloskey + Cohen, 1989)

Incremental learning: forgetting and rigidity

Catastrophic Forgetting

Tendency of a network to lose previously learned knowledge upon learning new information.

Catastrophic interference in connectionist networks: the sequential learning problem (McCloskey + Cohen, 1989)

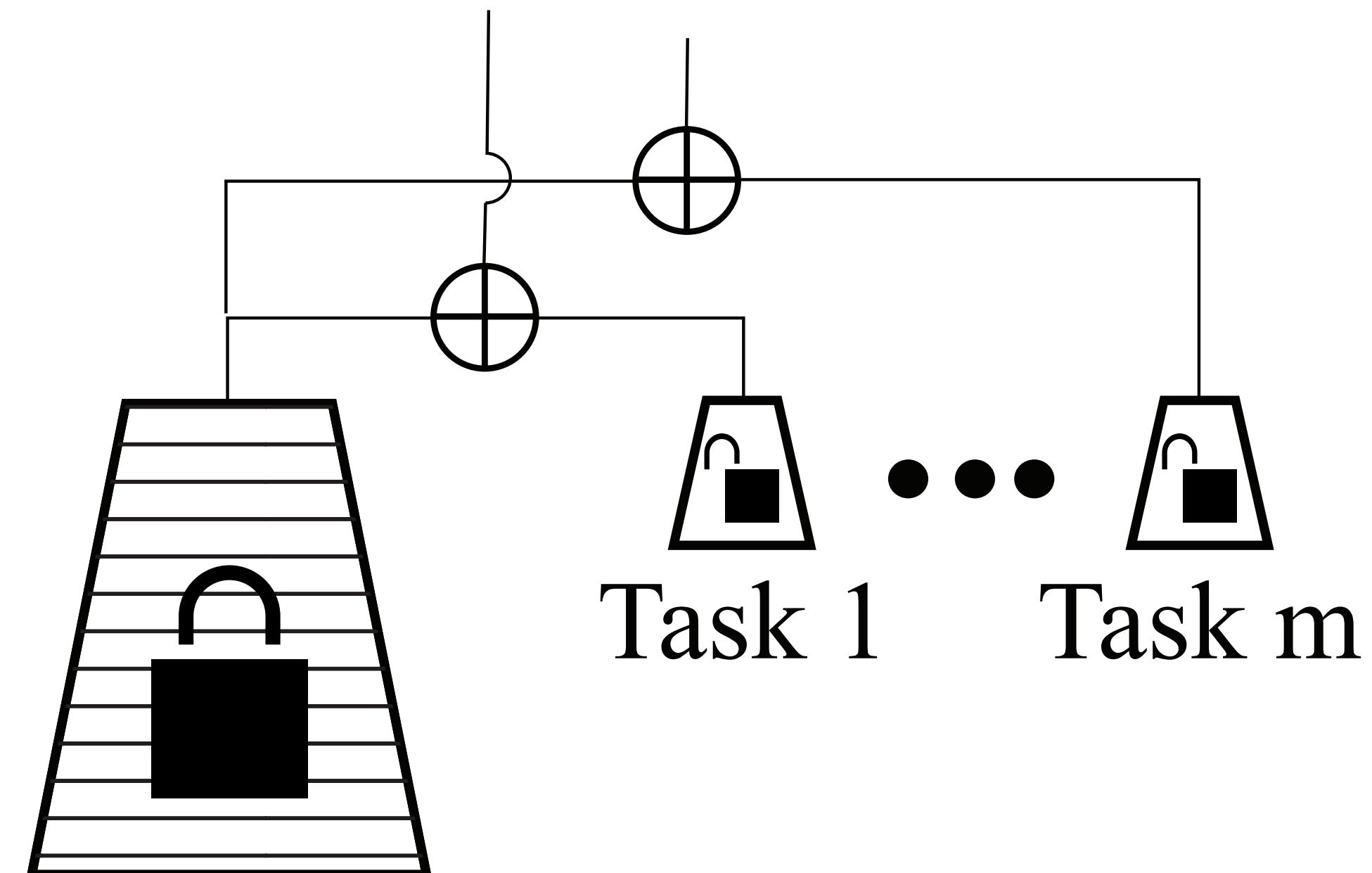
Rigidity (Intransigence)

Increasing inability of a network to adapt to new problems as it accrues constraints from previous problems.

The concept of rigidity: an enigma (Len, 1983)
Riemannian walk for incremental learning: understanding forgetting and intransigence (Chaudhry et al 2018)

Side-tuning for incremental learning

Architecture



Incremental learning: forgetting and rigidity

Catastrophic Forgetting

Tendency of a network to lose previously learned knowledge upon learning new information.

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Side-tuning: no forgetting + no rigidity

Incremental learning datasets: tasks

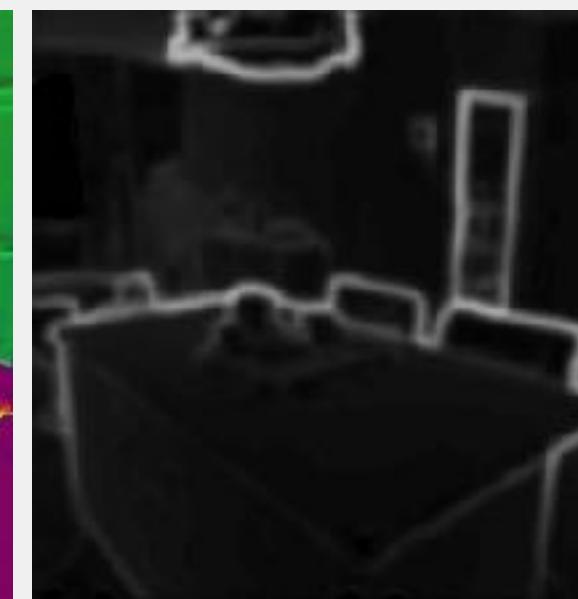
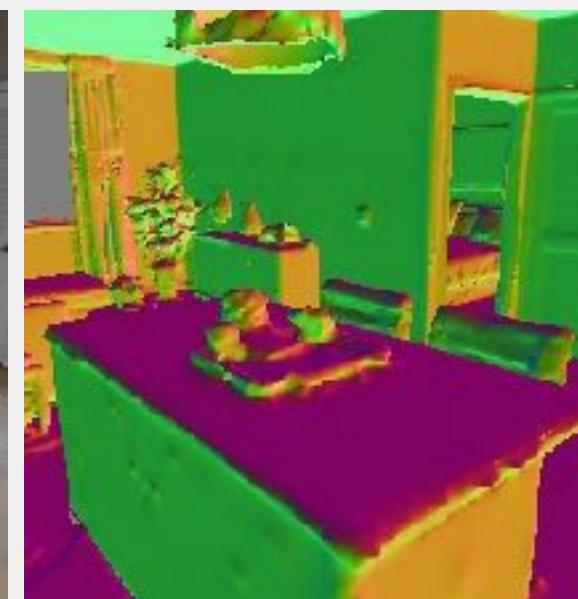
iTaskonomy

Zamir et al.

—

512x512 images

12 tasks



Autoencoding →

**Normals
Estimation**



**Occlusion
Edges**



**100-way
object classification:**

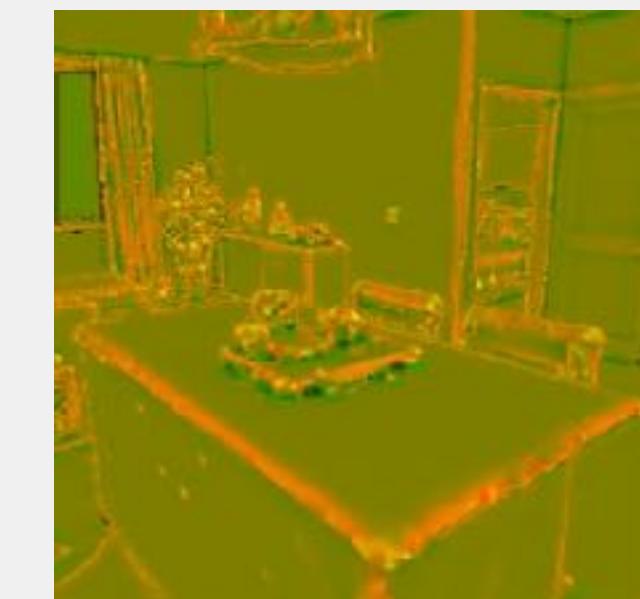
Curvature



**63-way
scene classification:**

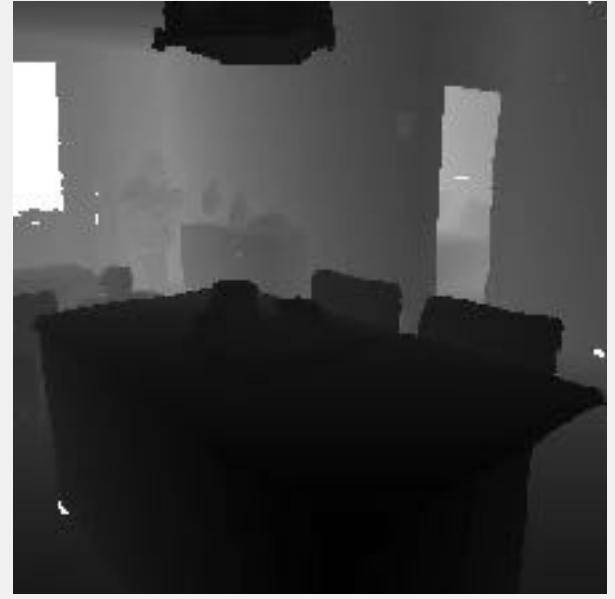
...

**Depth
Estimation**



Answer: Table

Answer: Office



iCIFAR

Rebuffi et al.

—

32x32 images

20 tasks

**5-way
object classification:**

...

**5-way
object classification:**

Answer: Cup

Answer: Cow

Answer: Cloud

Answer: Lion

Answer: Train

Answer: Squirrel

...

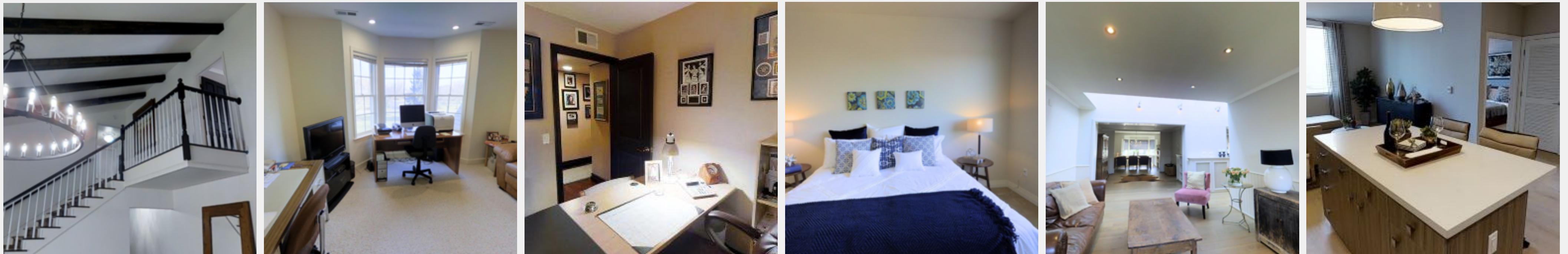
Answer: Butterfly

Incremental learning datasets: query images

iTaskonomy

Zamir et al.

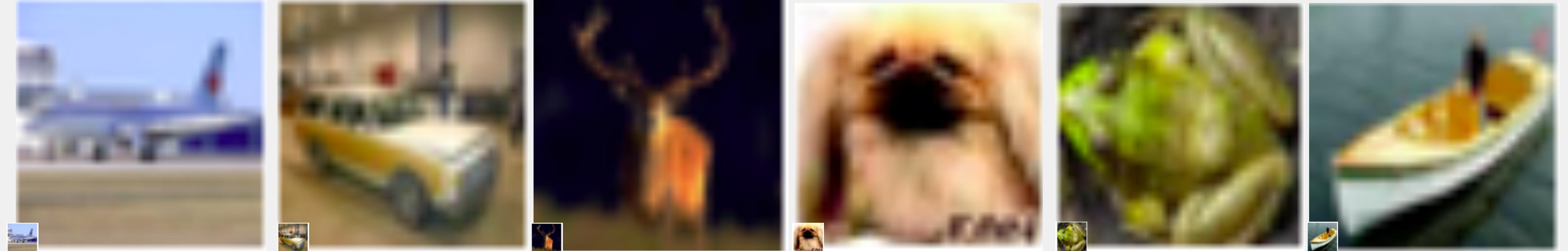
—
512x512 images
12 tasks



iCIFAR

Rebuffi et al.

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32x32 images
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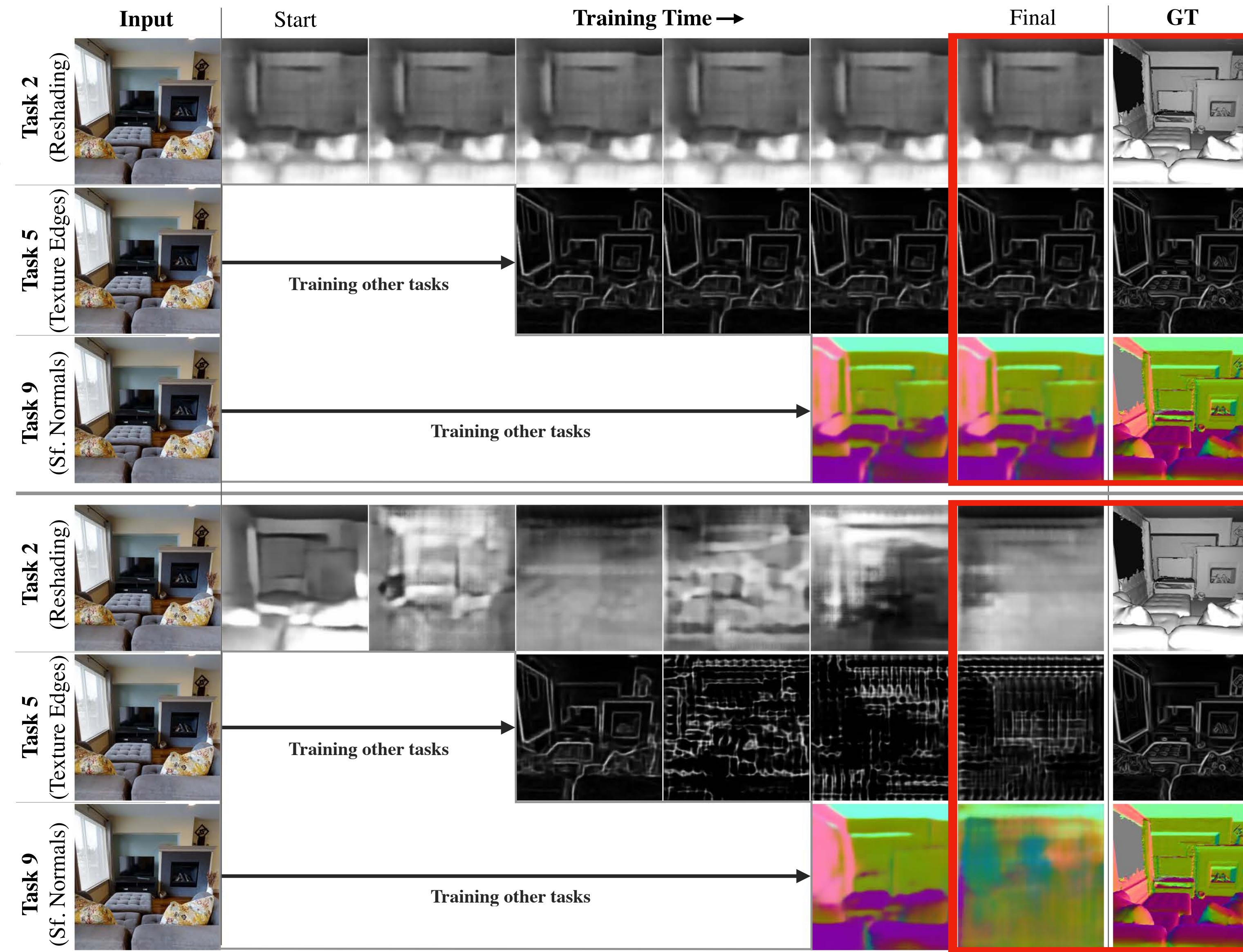


Trends shift on harder datasets: “Which Tasks Should Be Learned Together in Multi-task Learning?” Standley et al (ICML 2020)

Evaluation on iTaskonomy

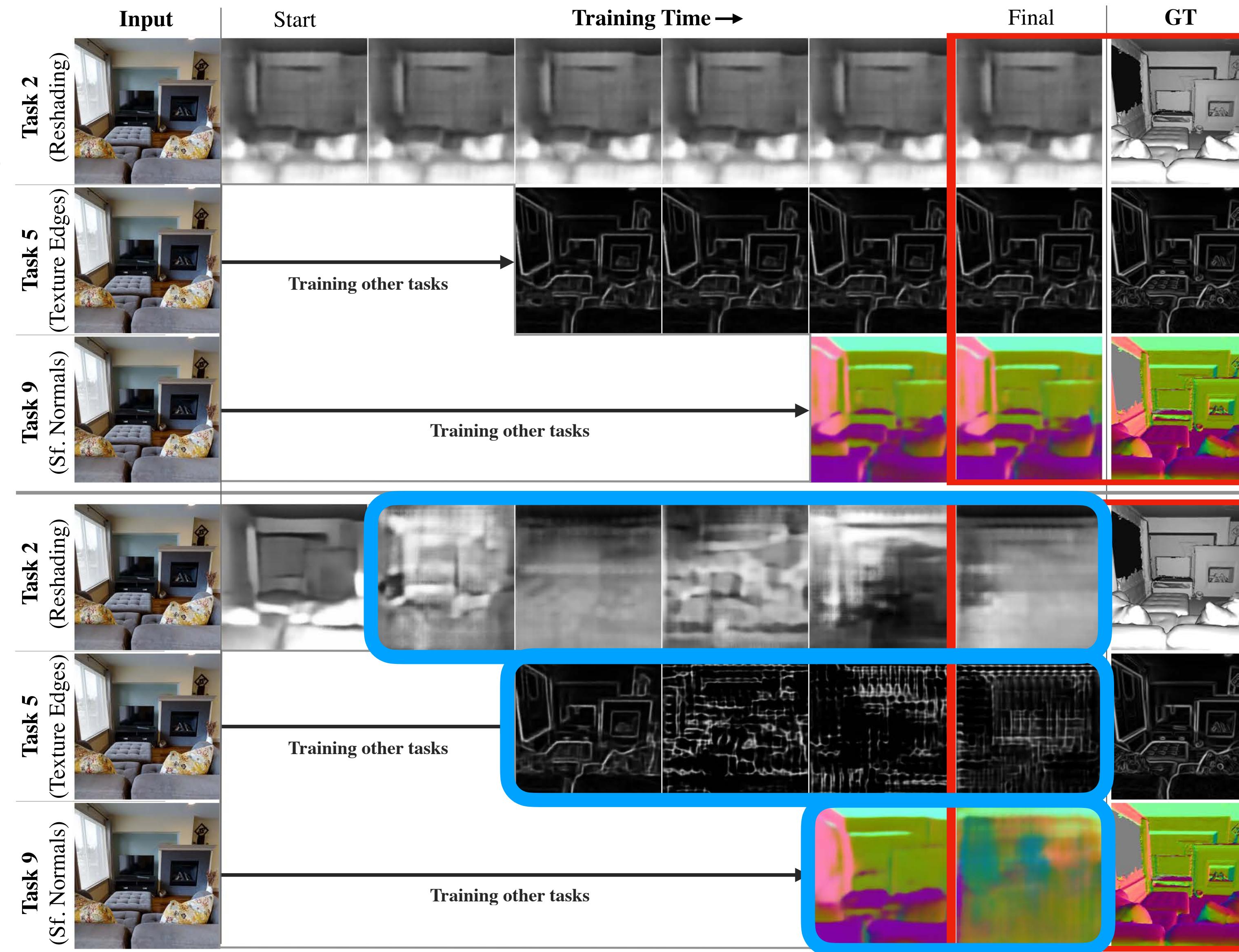
Side-Tuning

Elastic Weight Consolidation

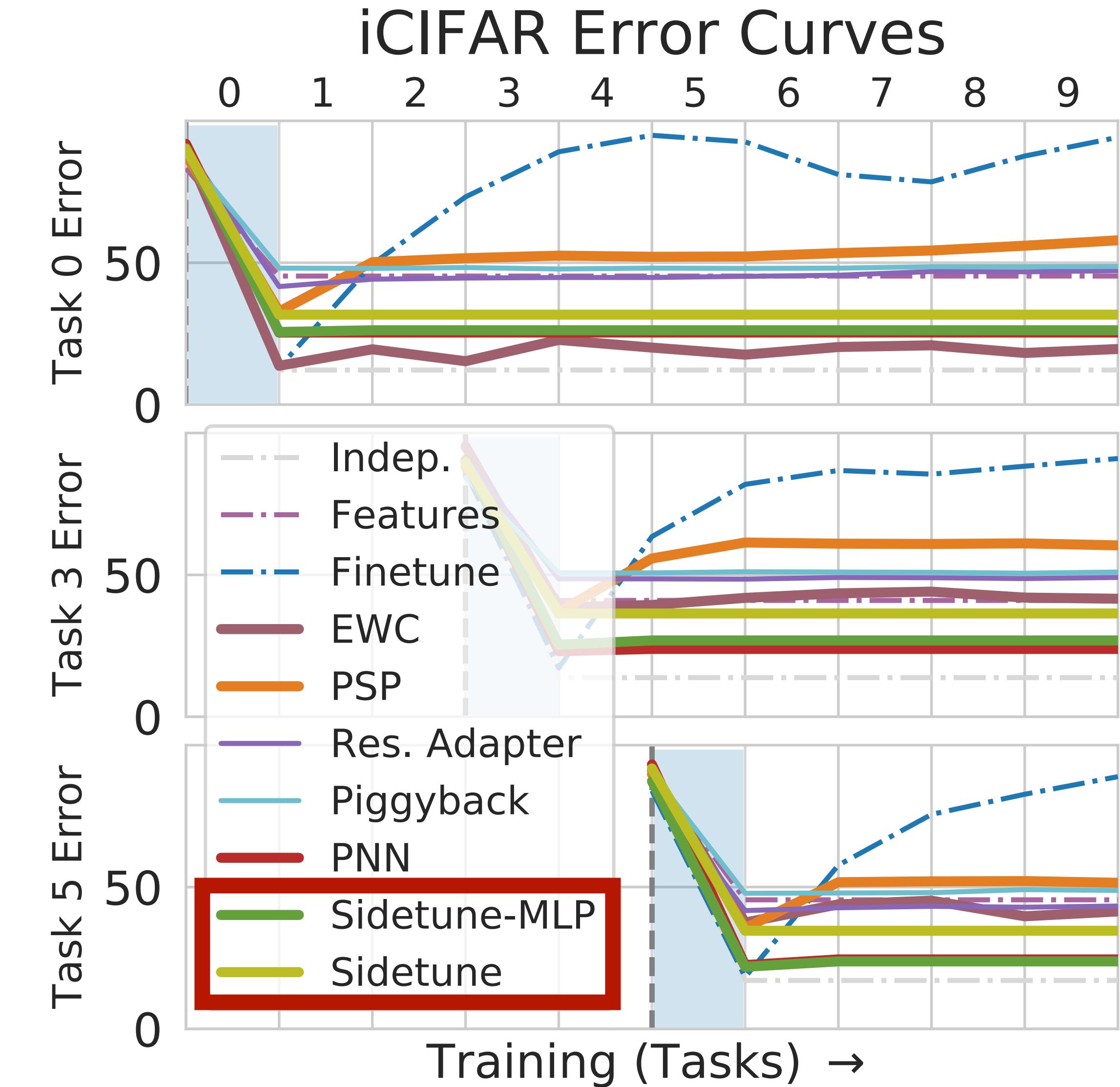
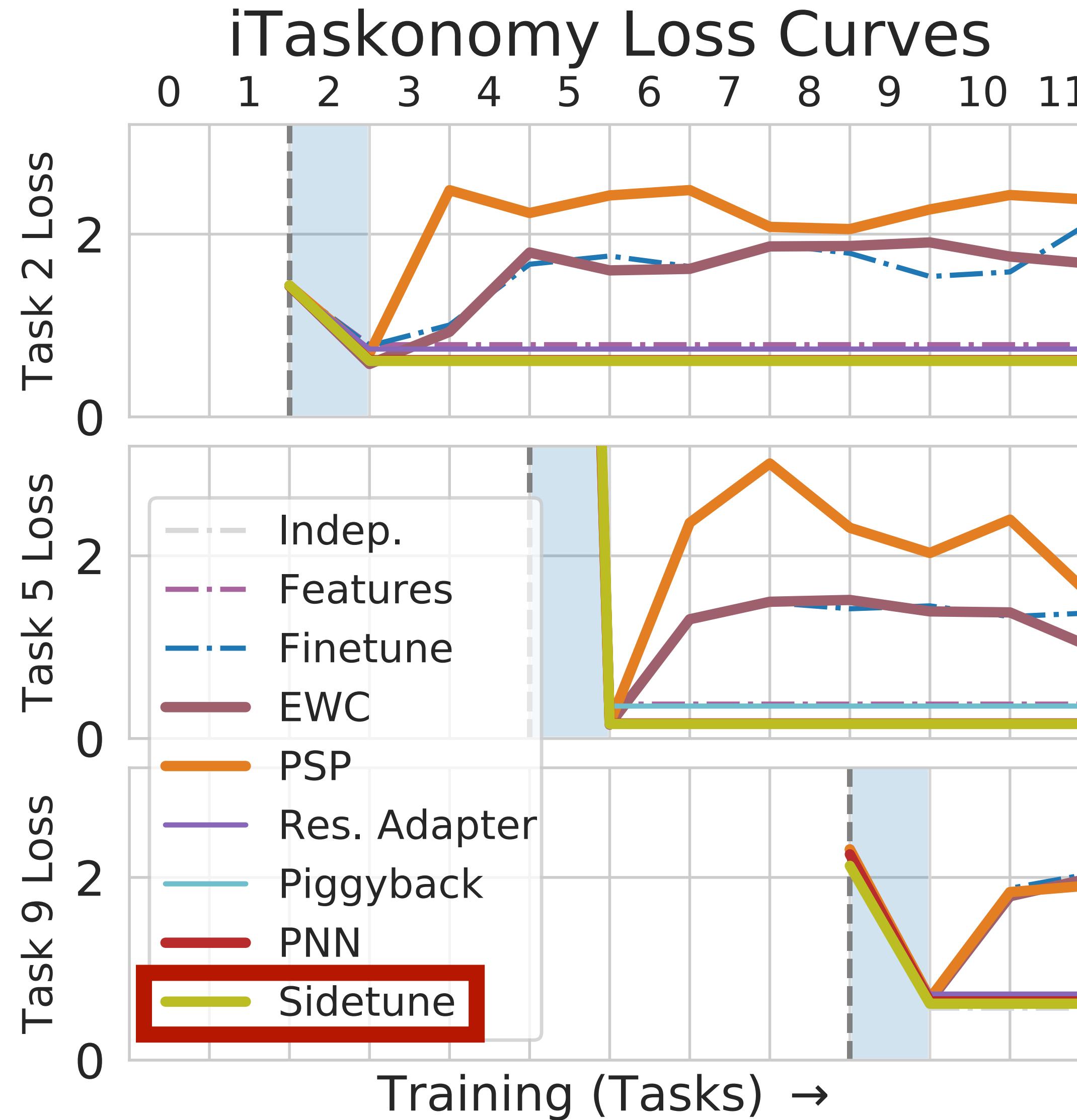


Evaluation on iTaskonomy

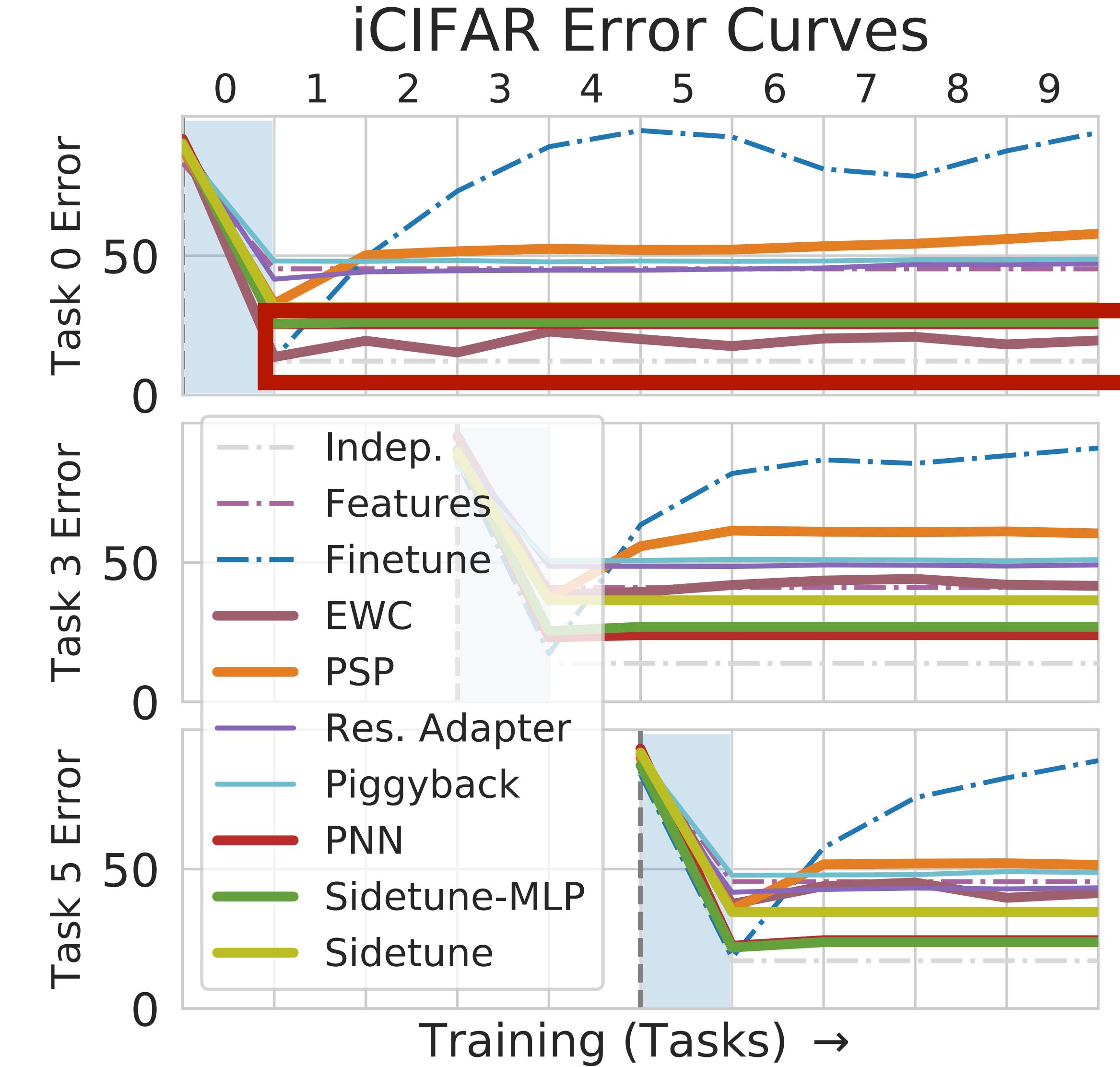
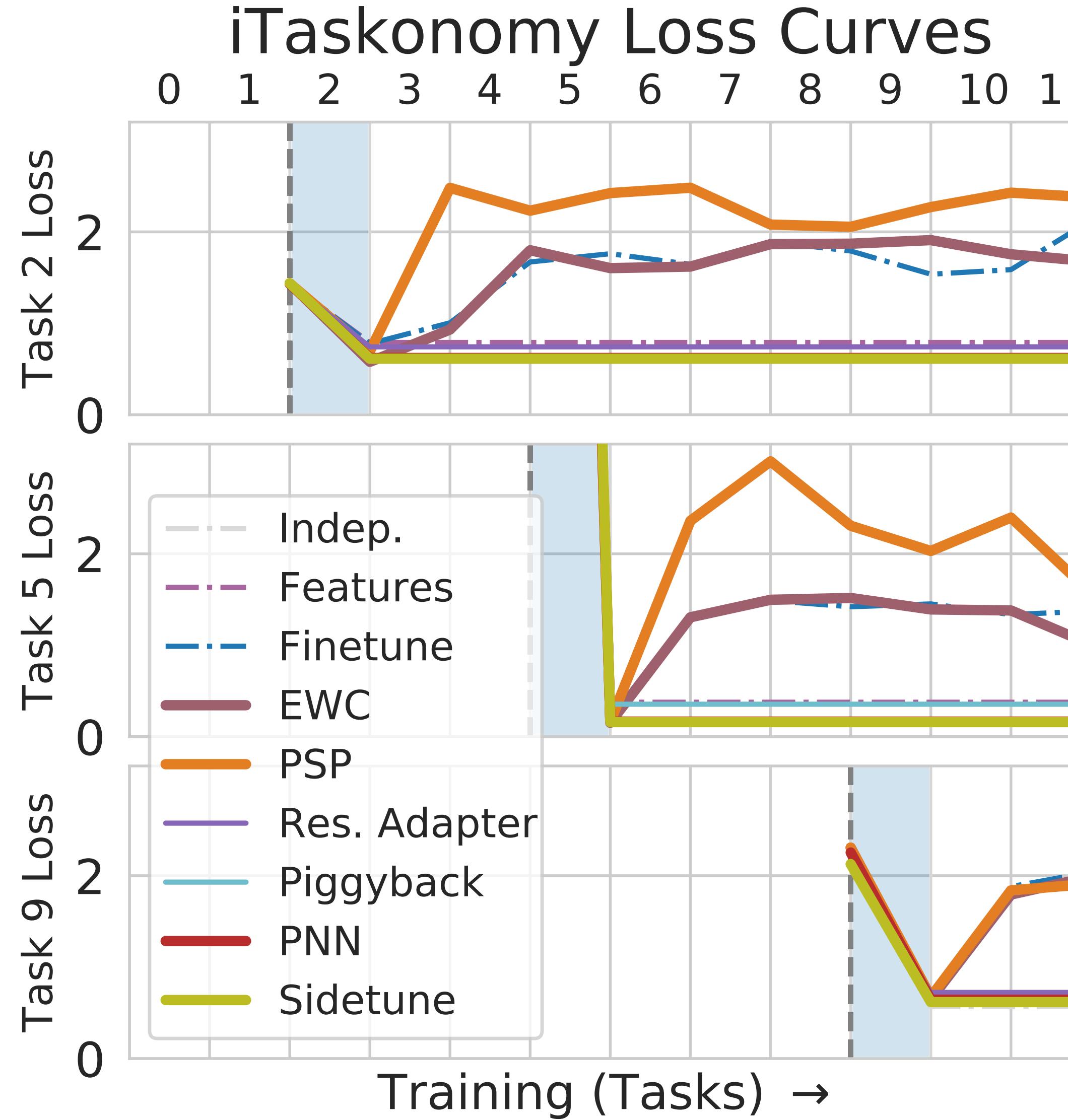
Side-Tuning



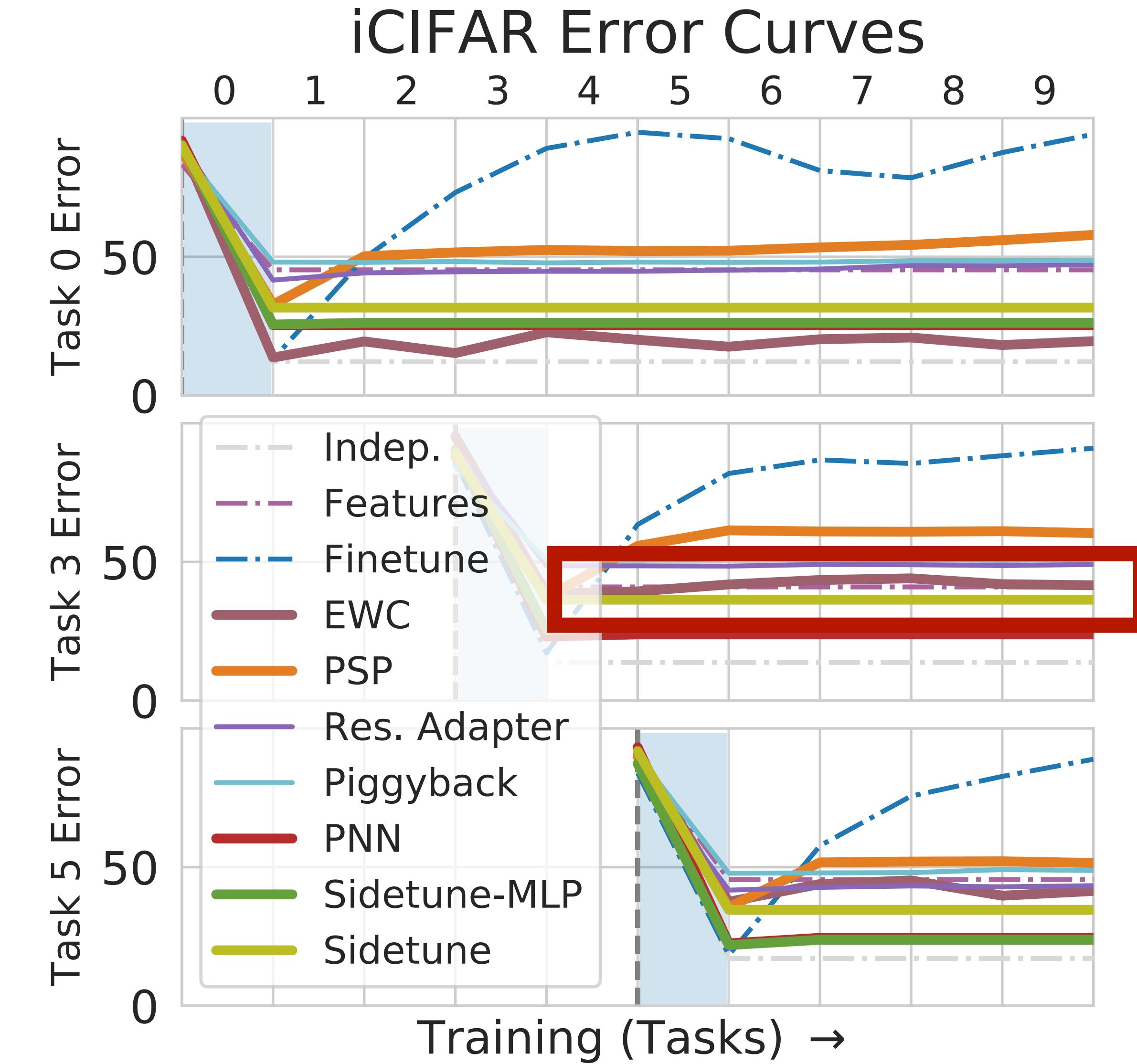
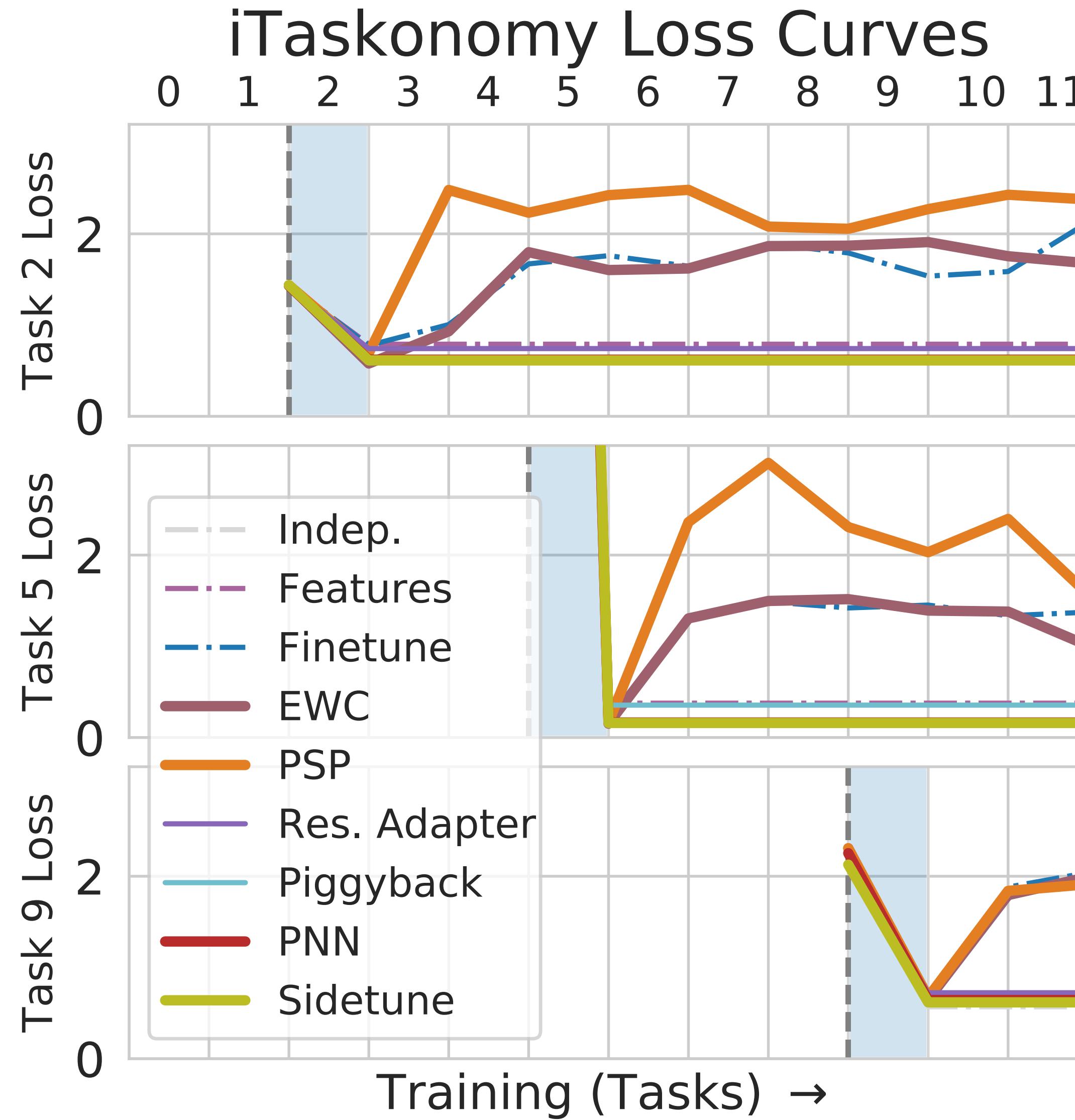
Results: catastrophic forgetting in incremental learning



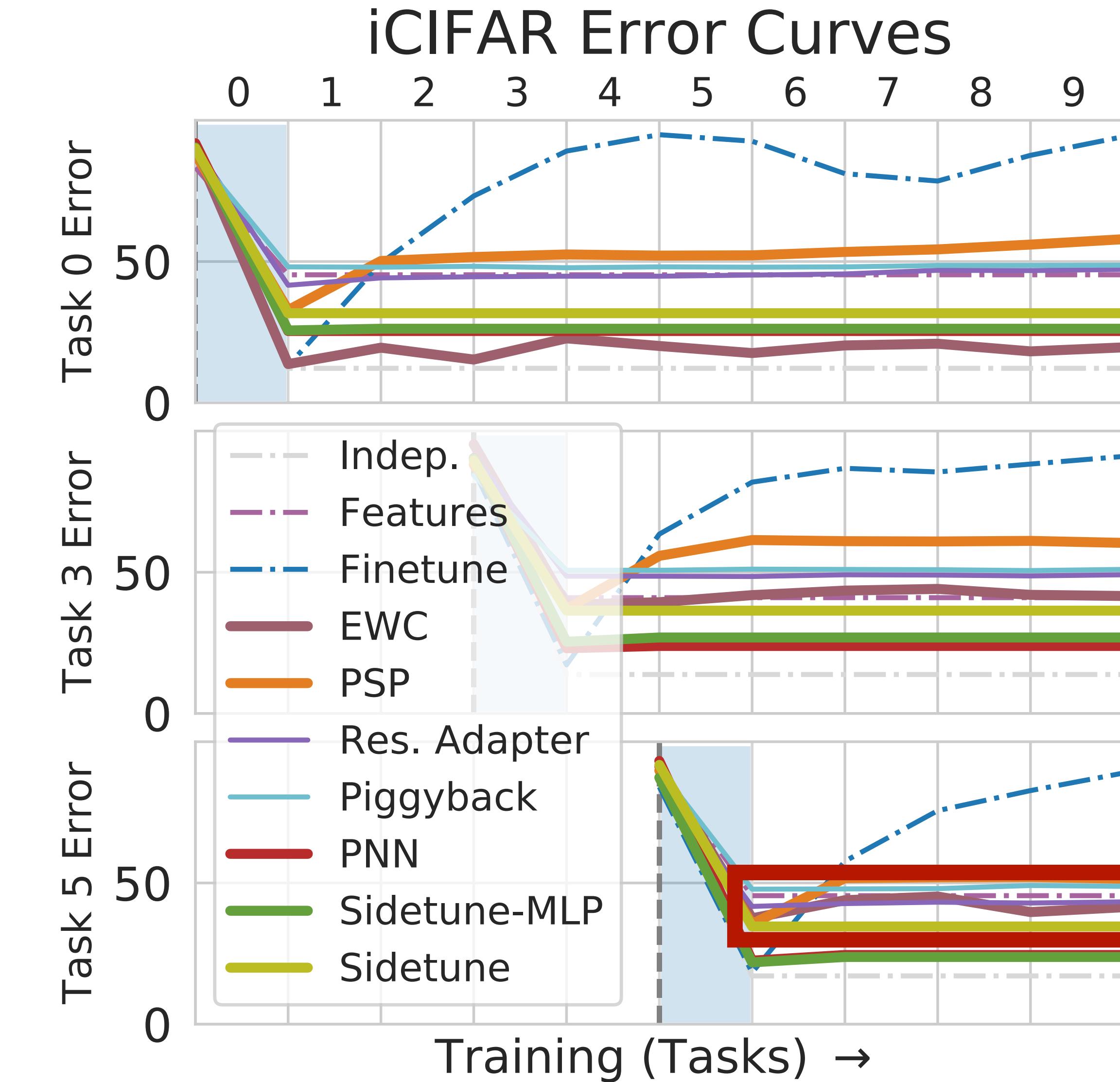
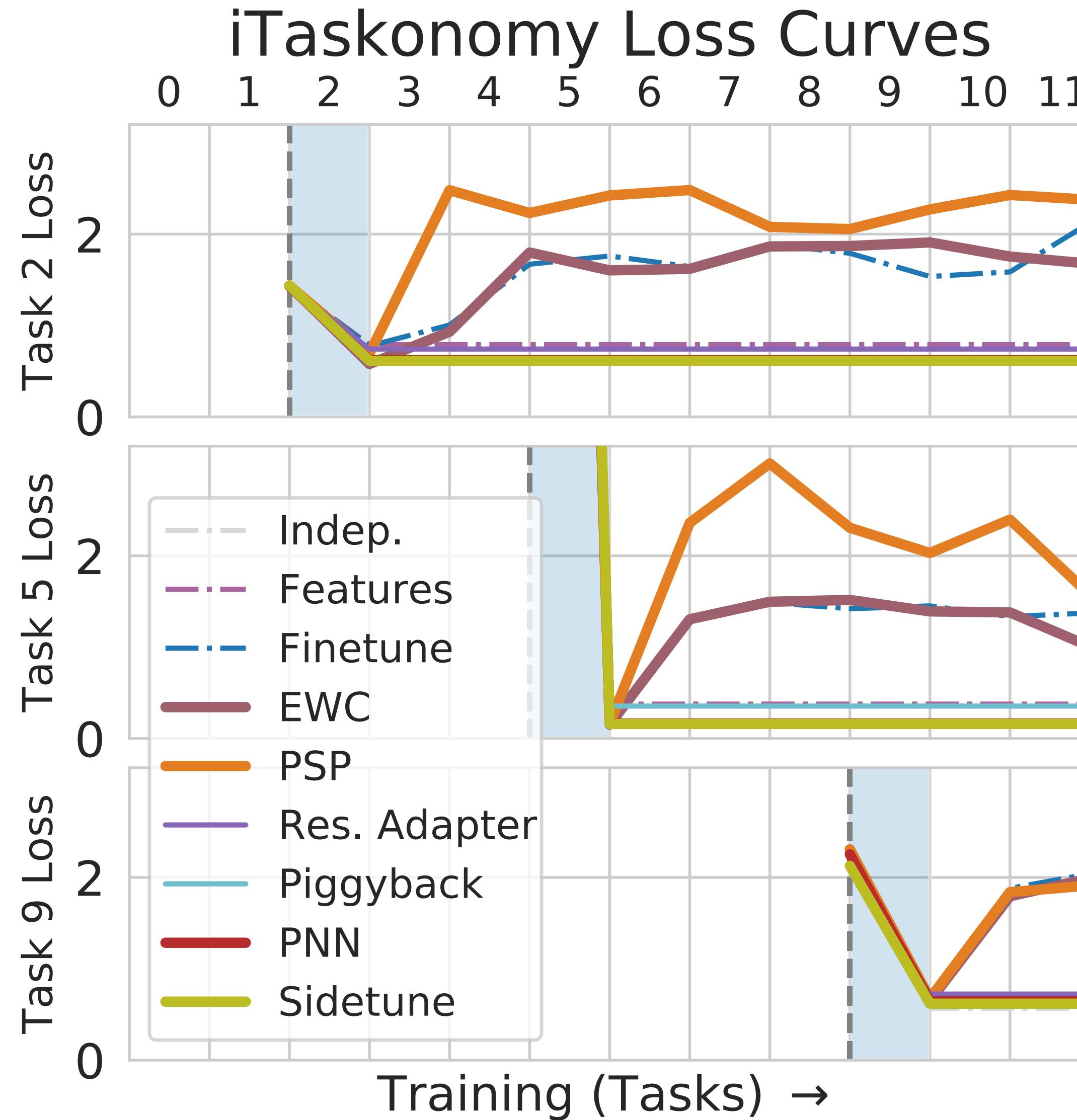
Results: catastrophic forgetting in incremental learning



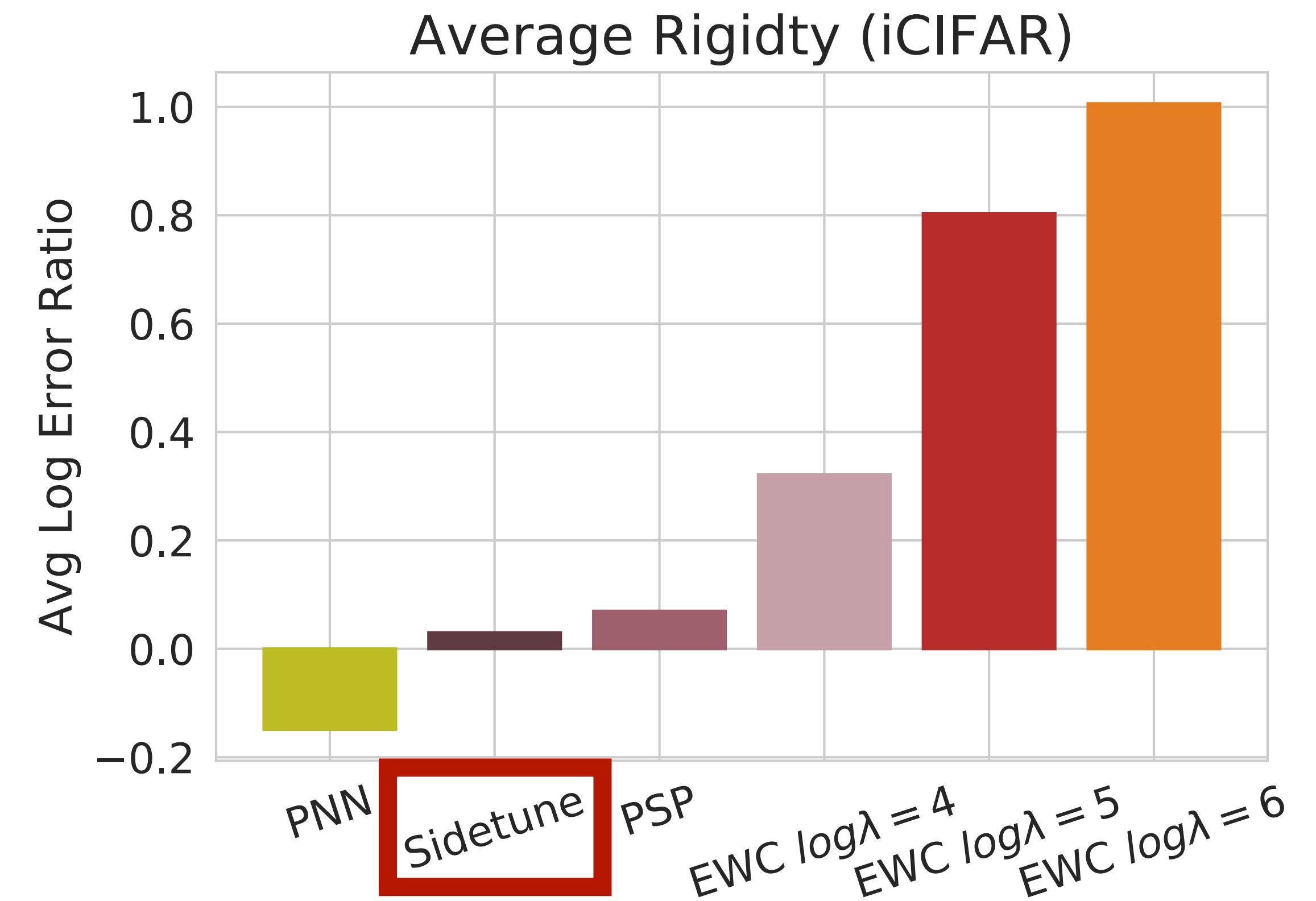
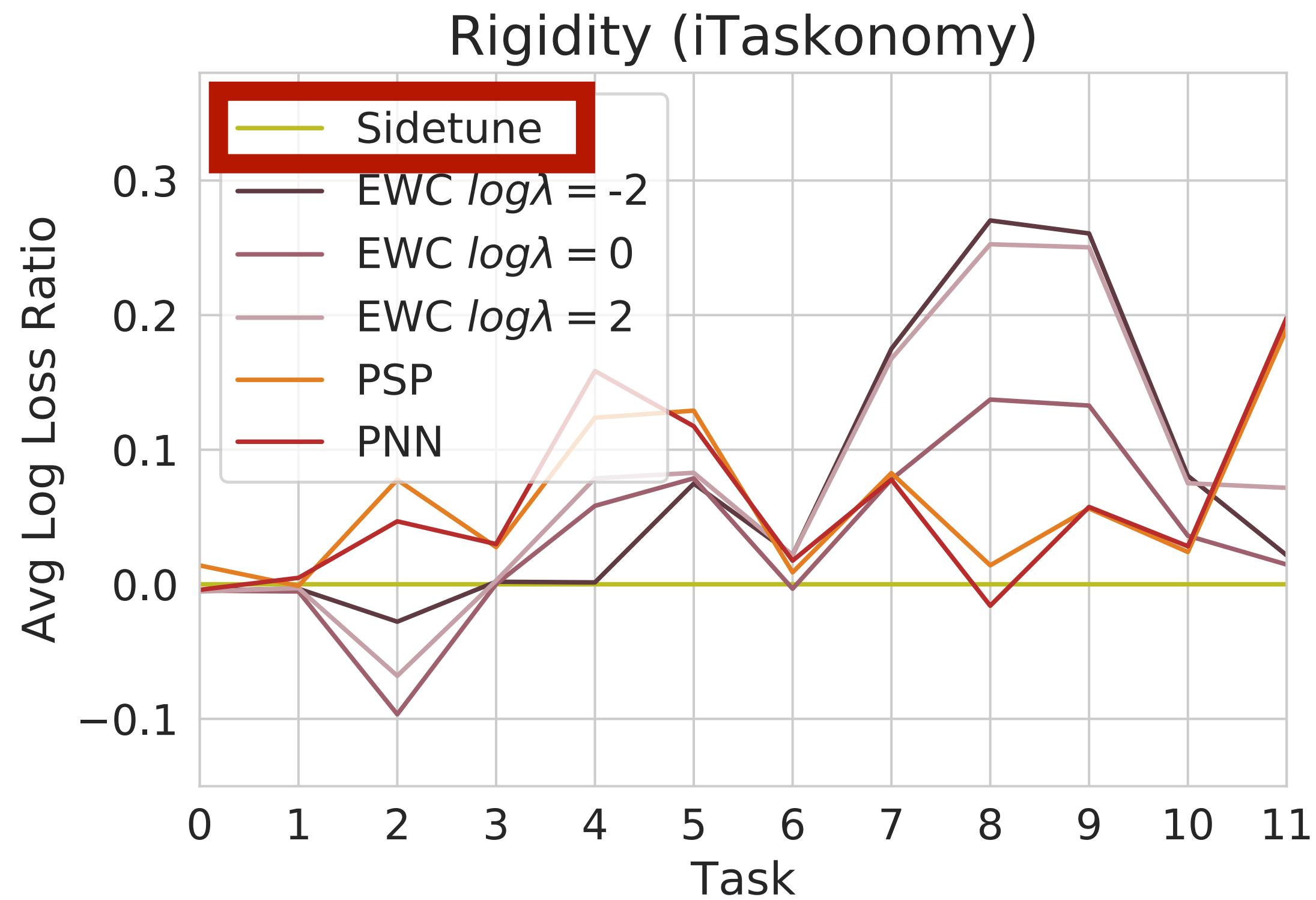
Results: catastrophic forgetting in incremental learning



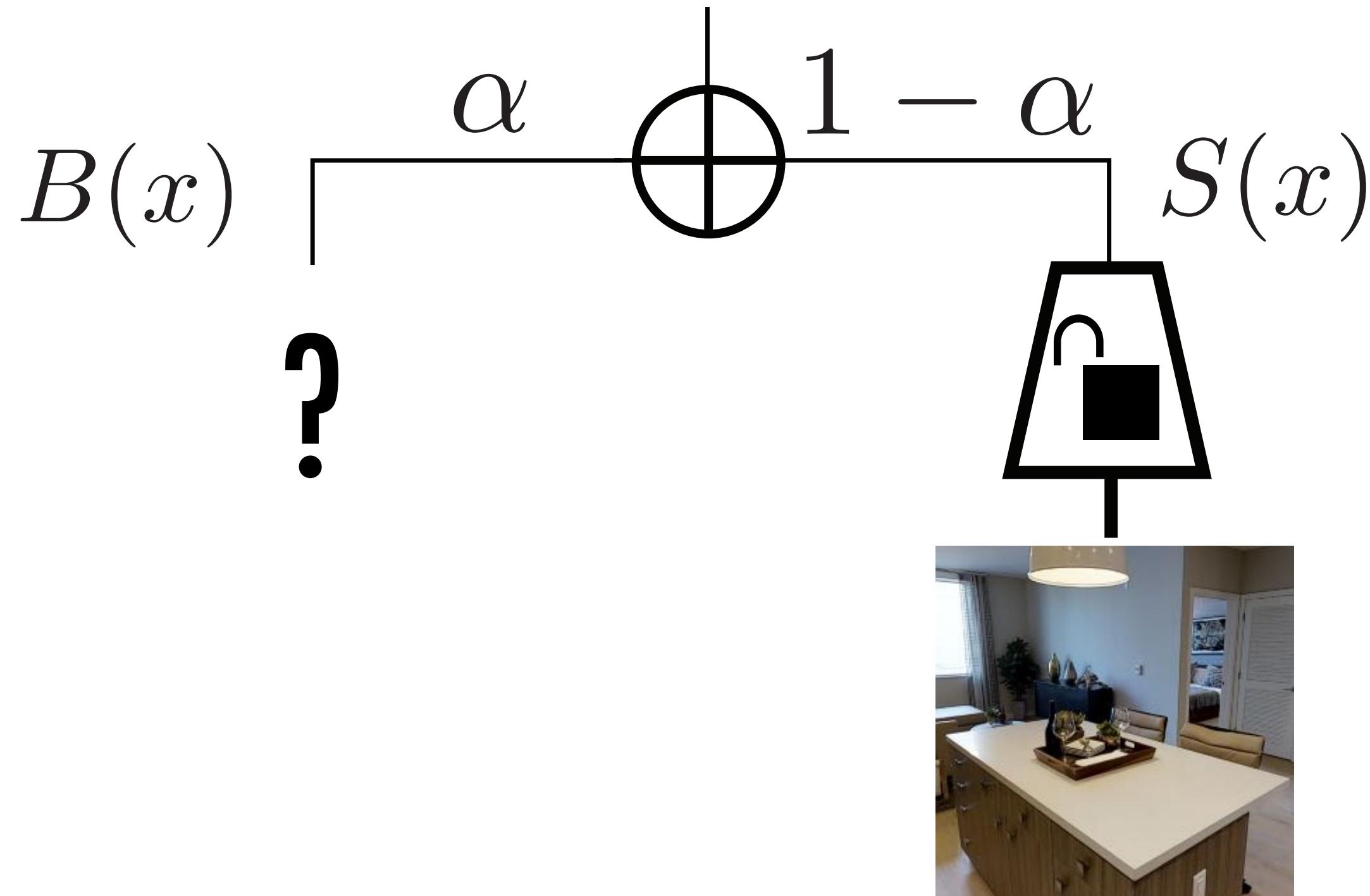
Results: catastrophic forgetting in incremental learning



Results: rigidity in incremental learning



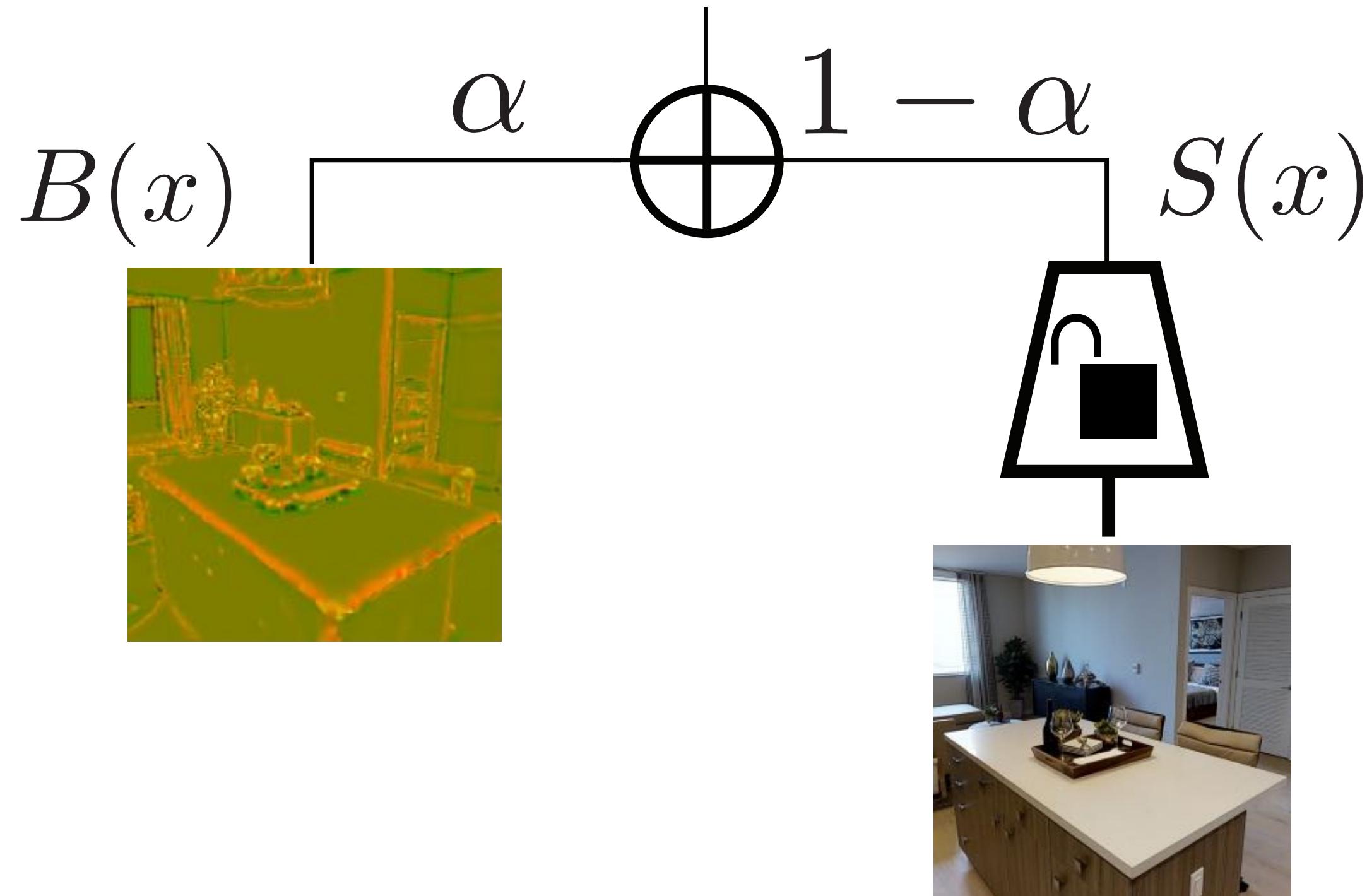
Side-Tuning: Beyond Network Adaptation



- Base model needn't be a network
- Decision tree, or oracle for some other task



Side-Tuning: Beyond Network Adaptation

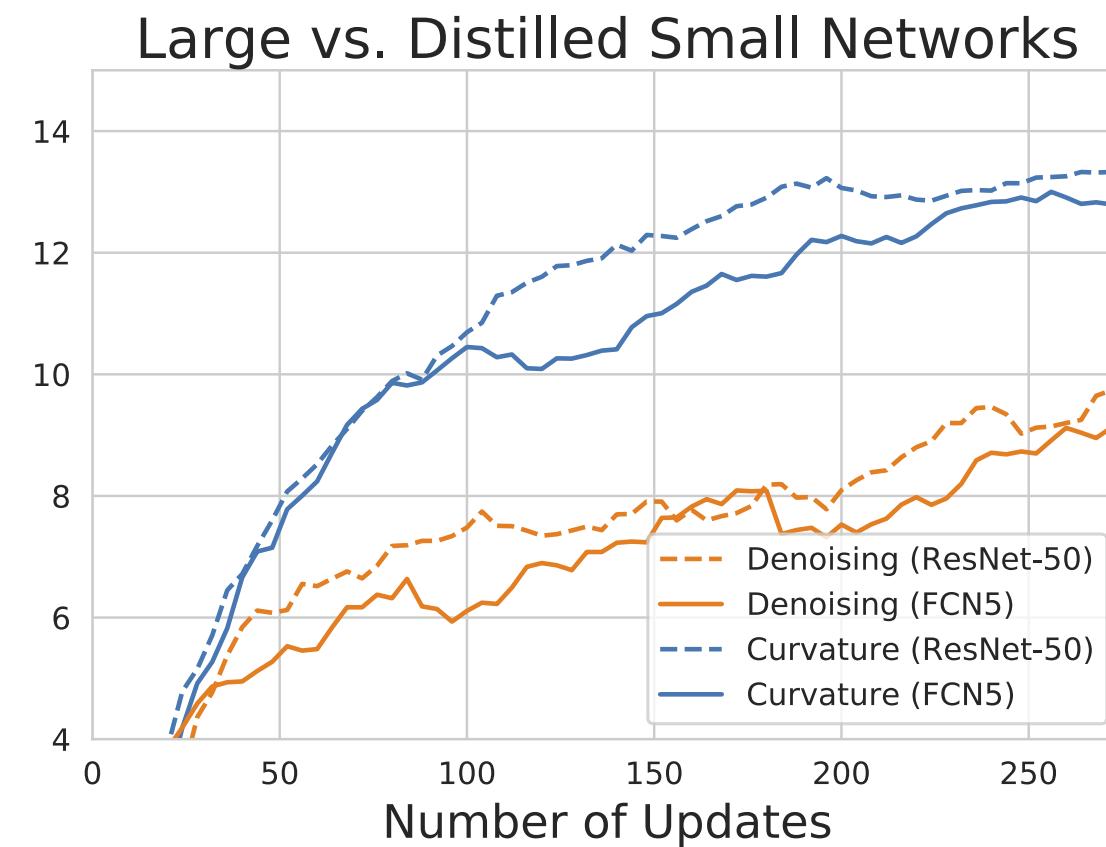


- Base model needn't be a network
- Decision tree, or oracle for some other task
- Can actual curvature label
- Works really well.

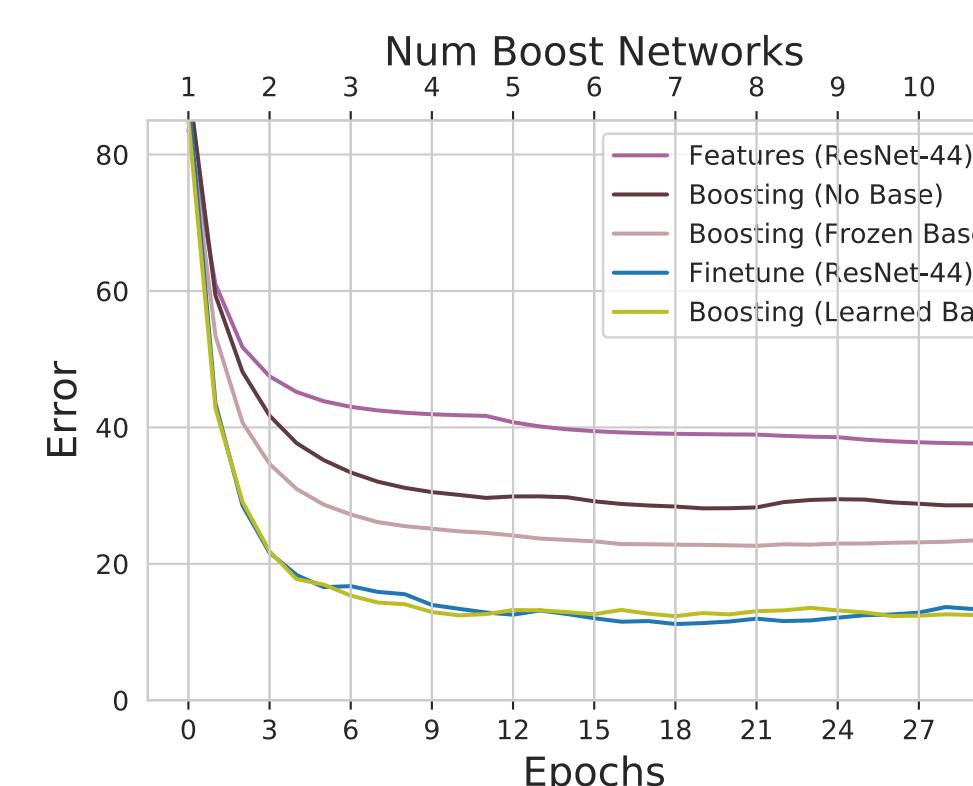
More in our paper + on the website:

sidetuning.berkeley.edu

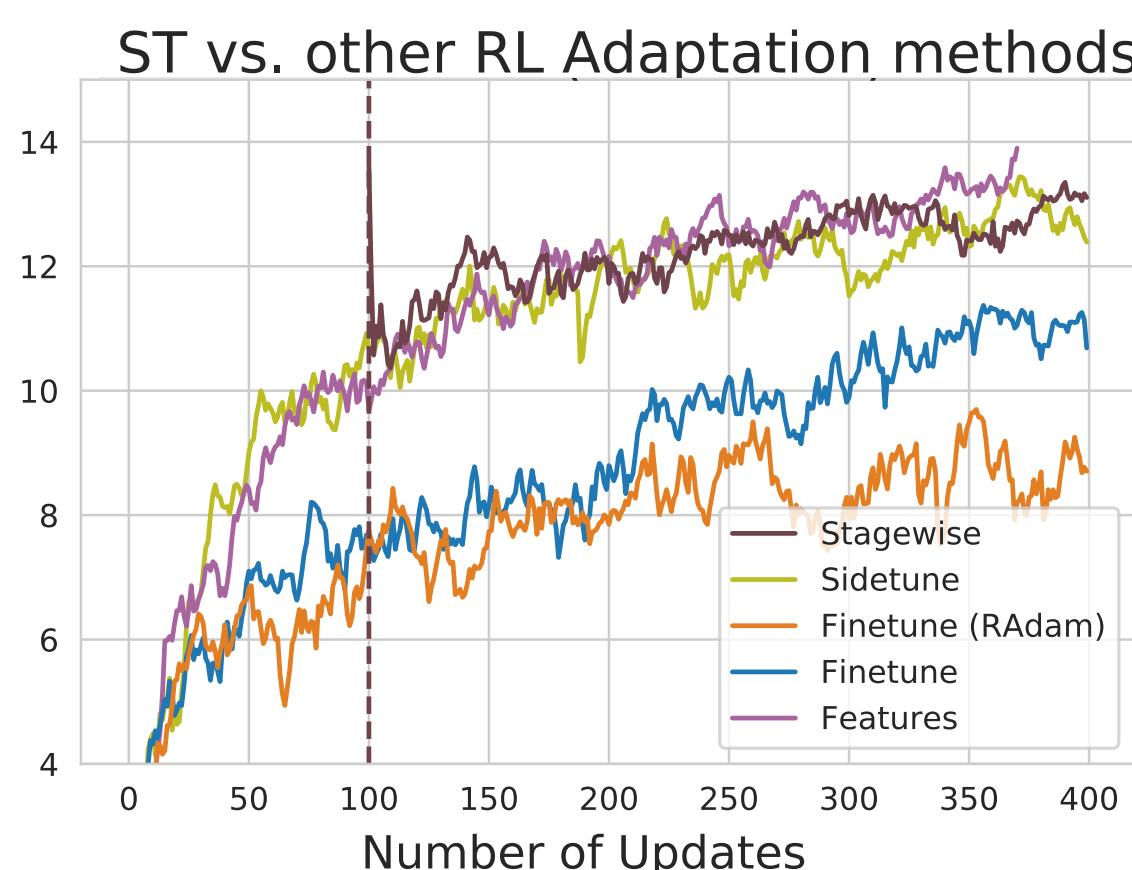
Analysis of network size:



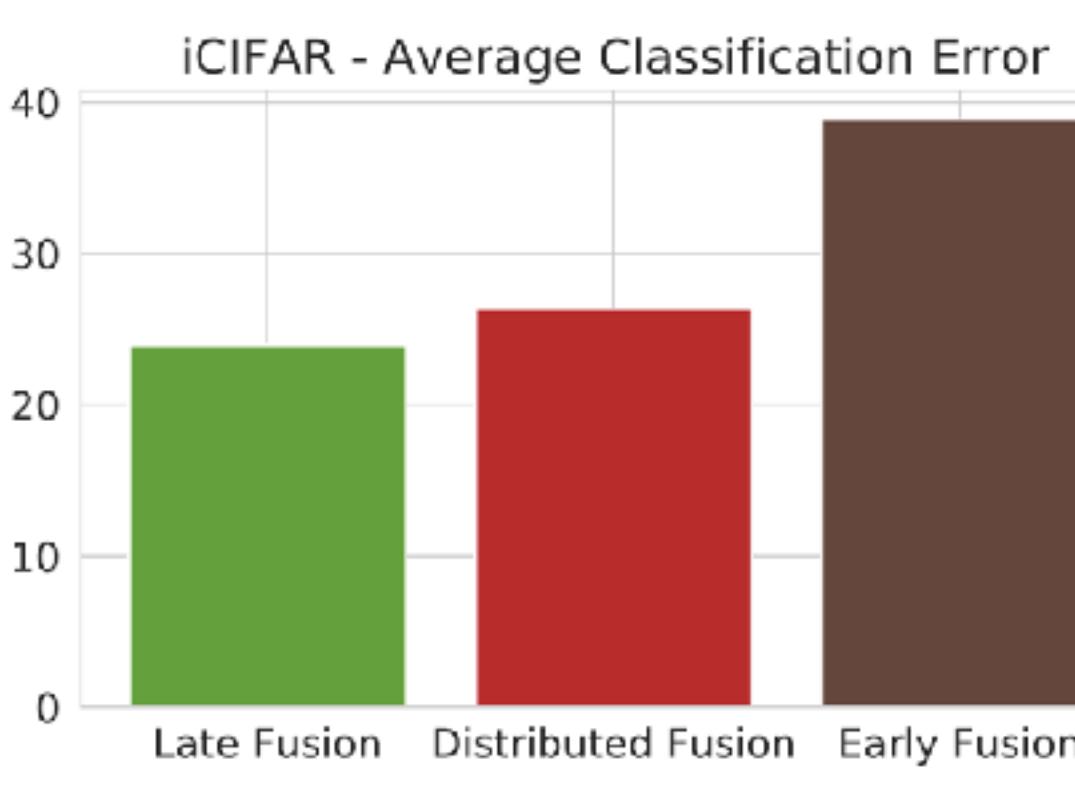
Comparison to boosting



Comparison to other adaptation methods in RL



Fusion: Early vs. Mid vs. Late



Ablation studies with different design choices

Method	Avg. Rank (\downarrow) iTaskonomy
Product (Element-wise)	3.64
Summation (α -blending)	2.27
MLP [29]	2.18
FiLM [21]	1.91

Method	Avg. Rank (\downarrow) iTaskonomy
Base-Only	2.55
Side-Only	2.10
Side-tuning	1.36

And more:

- Experiments with non-neural network base
- Analysis of α w.r.t. task relatedness
- Code (github repo)
- Environments to reproduce experiments (via docker)
- Full qualitative and quantitative results for all methods



Side-Tuning: A Baseline for Network Adaptation via Additive Side Networks

<http://sitetuning.berkeley.edu>



Berkeley
UNIVERSITY OF CALIFORNIA



STANFORD
UNIVERSITY

EPFL

Swiss Federal
Institute of
Technology



Jeffrey O. Zhang



Alexander Sax



Amir Zamir



Leonidas Guibas



Jitendra Malik