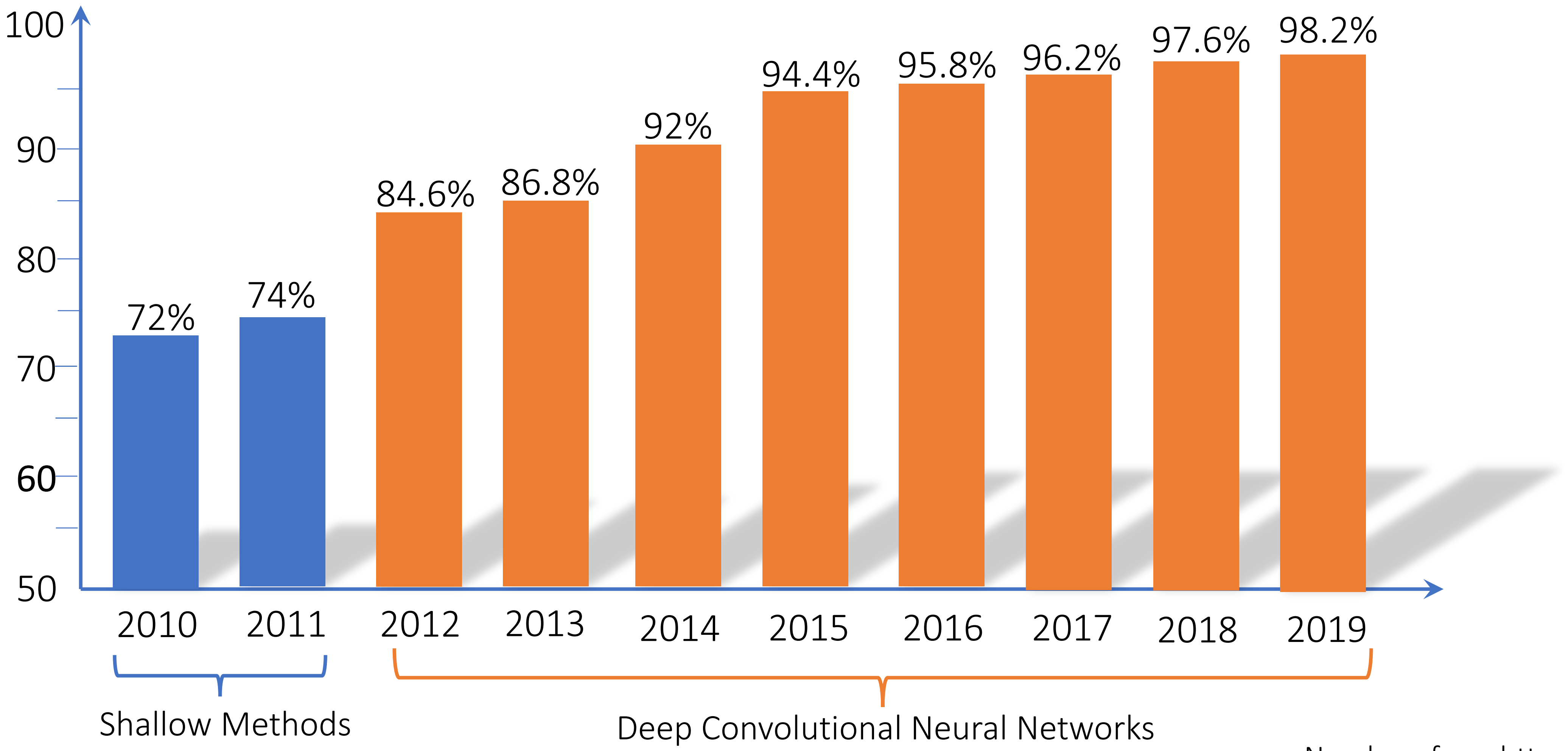
Adaptive (Dynamic) Neural Networks for Efficient Inference

Rogerio Schmidt Feris

Principal Research Scientist and Manager

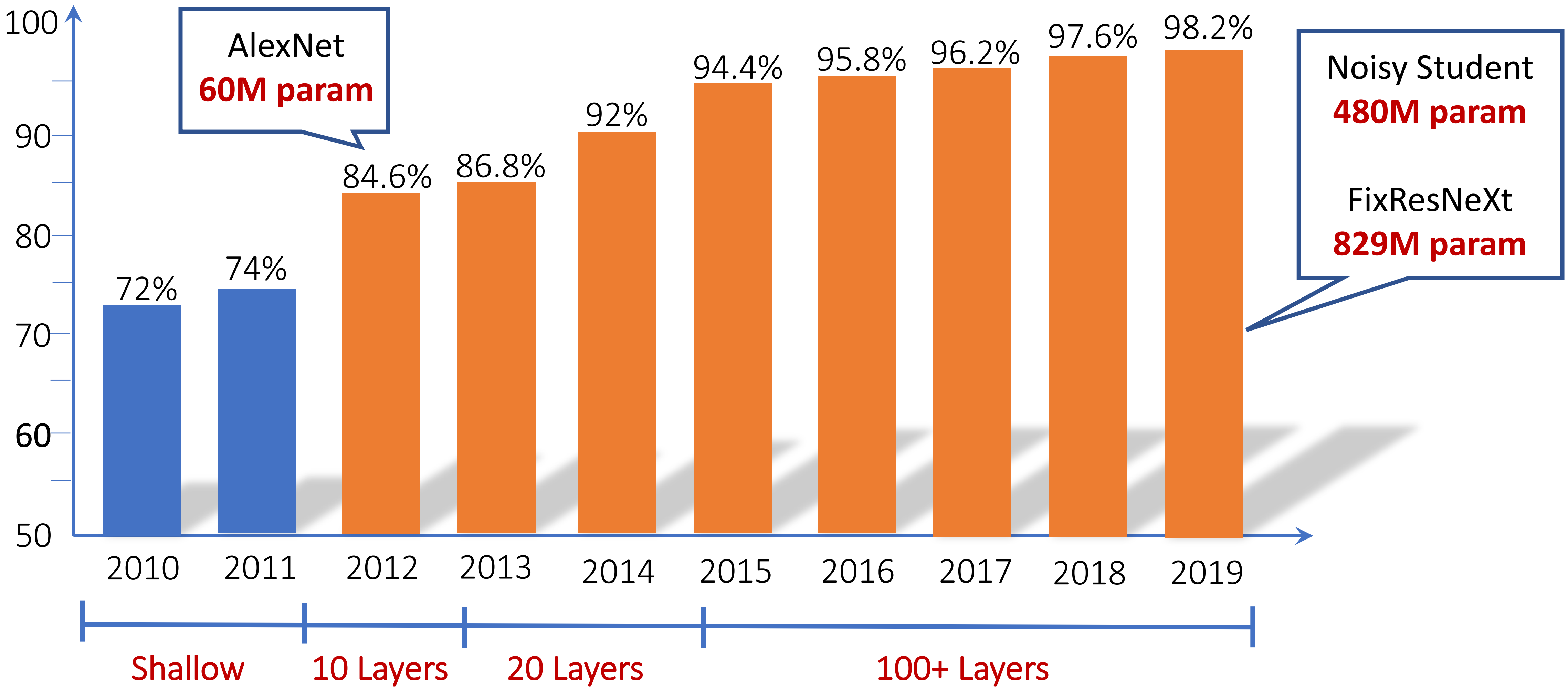
IBM Research & MIT-IBM Watson AI Lab

ImageNet Classification (top-5 accuracy)



Numbers from http://paperswithcode.com

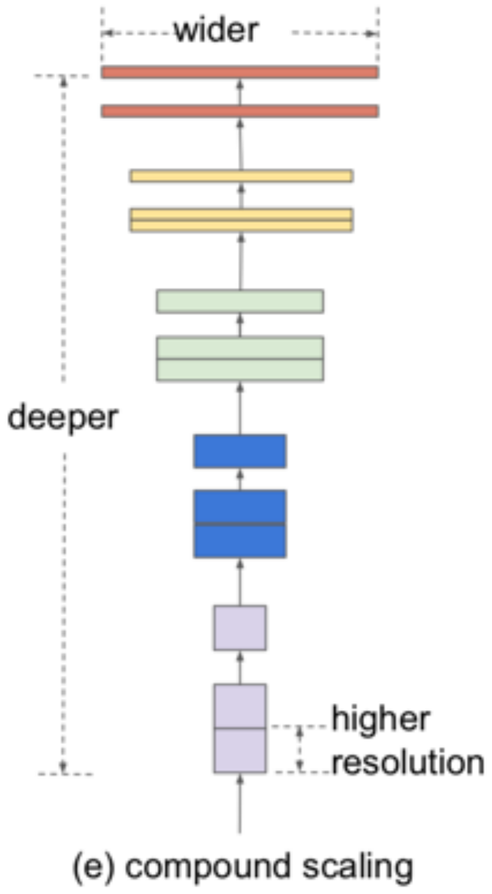
Better Results → More Complexity



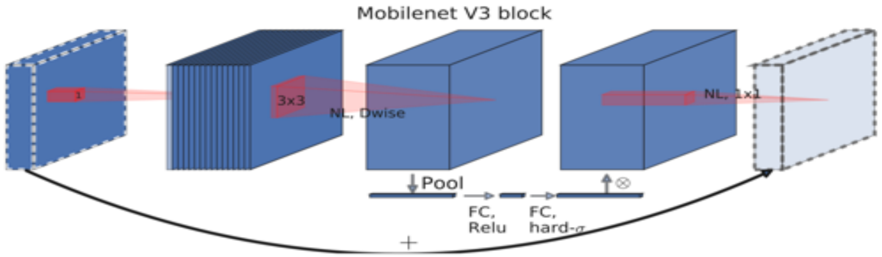
Model Compression and Acceleration

- Low-rank factorization, Knowledge Distillation, Pruning, Quantization, Neural Architecture Search, etc.

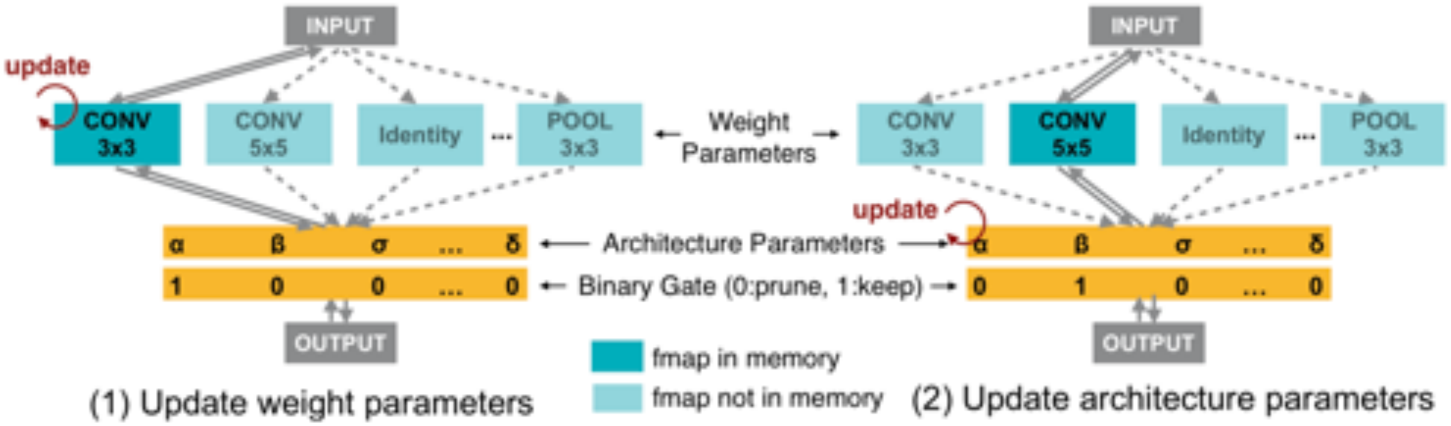
EfficientNet [Tan & Le, 2019]



MobileNet V3 [Howard et al, 2019]



ProxylessNAS [Cai et al, 2019]

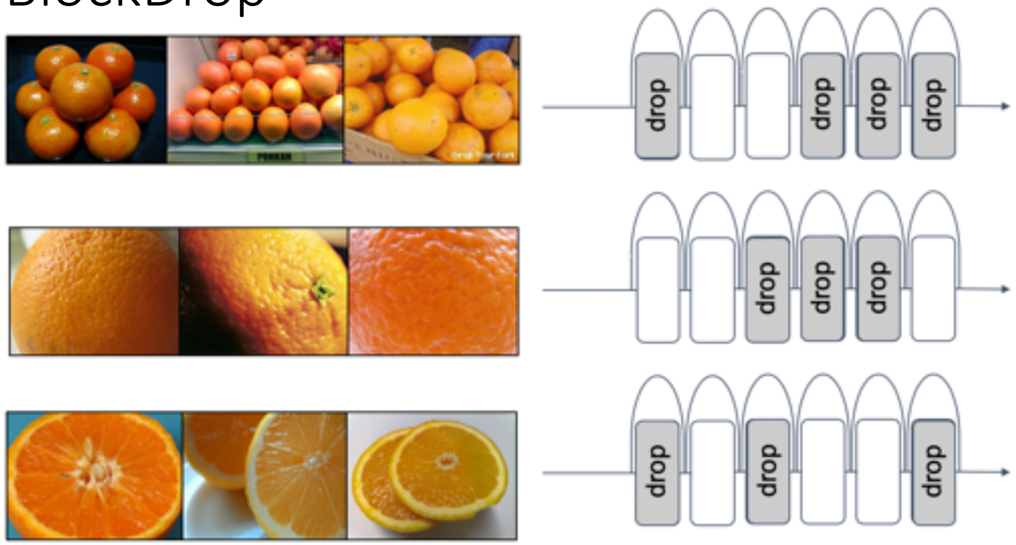


Most methods rely on one-size-fits-all networks that require the same fixed set of features to be extracted for all inputs, no matter their complexity

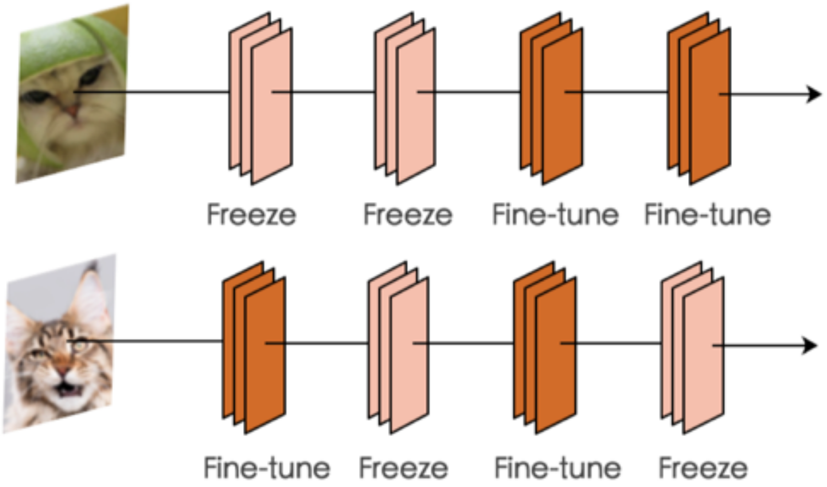
This talk: Speeding up Deep Neural Networks through Adaptive Computation

- Networks models that are dynamically reconfigured depending on the input

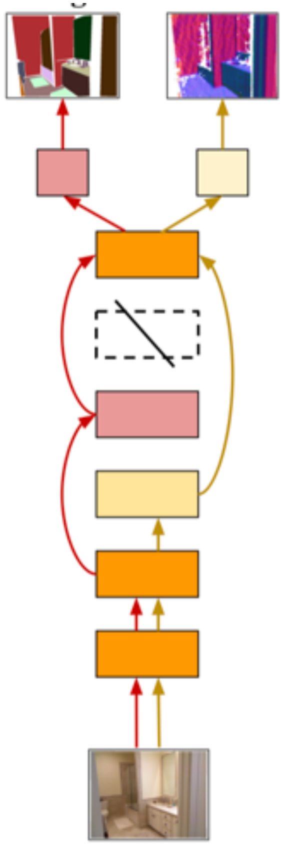
BlockDrop



SpotTune

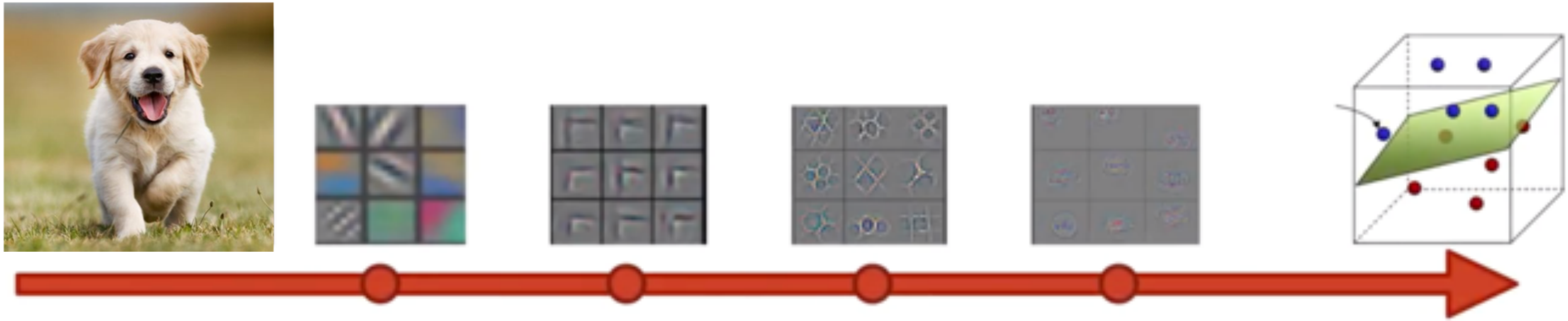


AdaShare



- Conditional Computation [Bengio et al, 2013/2016]

Feed-Forward Convolutional Neural Networks



Adapted from Veit et al

Feed-Forward Convolutional Neural Networks

What happens when we delete a step?

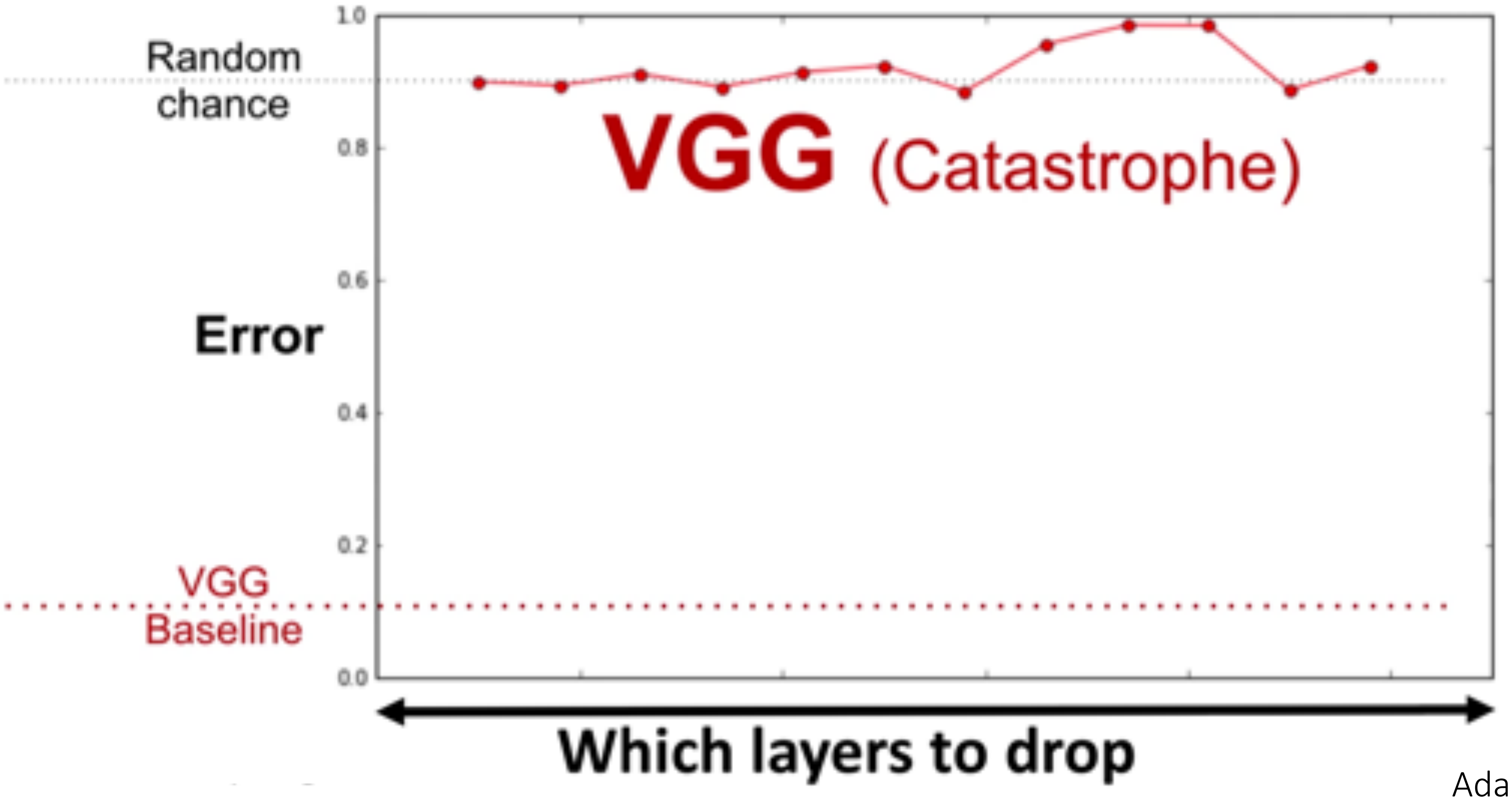
Adapted from Veit et al

Feed-Forward Convolutional Neural Networks

Adapted from Veit et al

What happens if we delete a layer at test time?

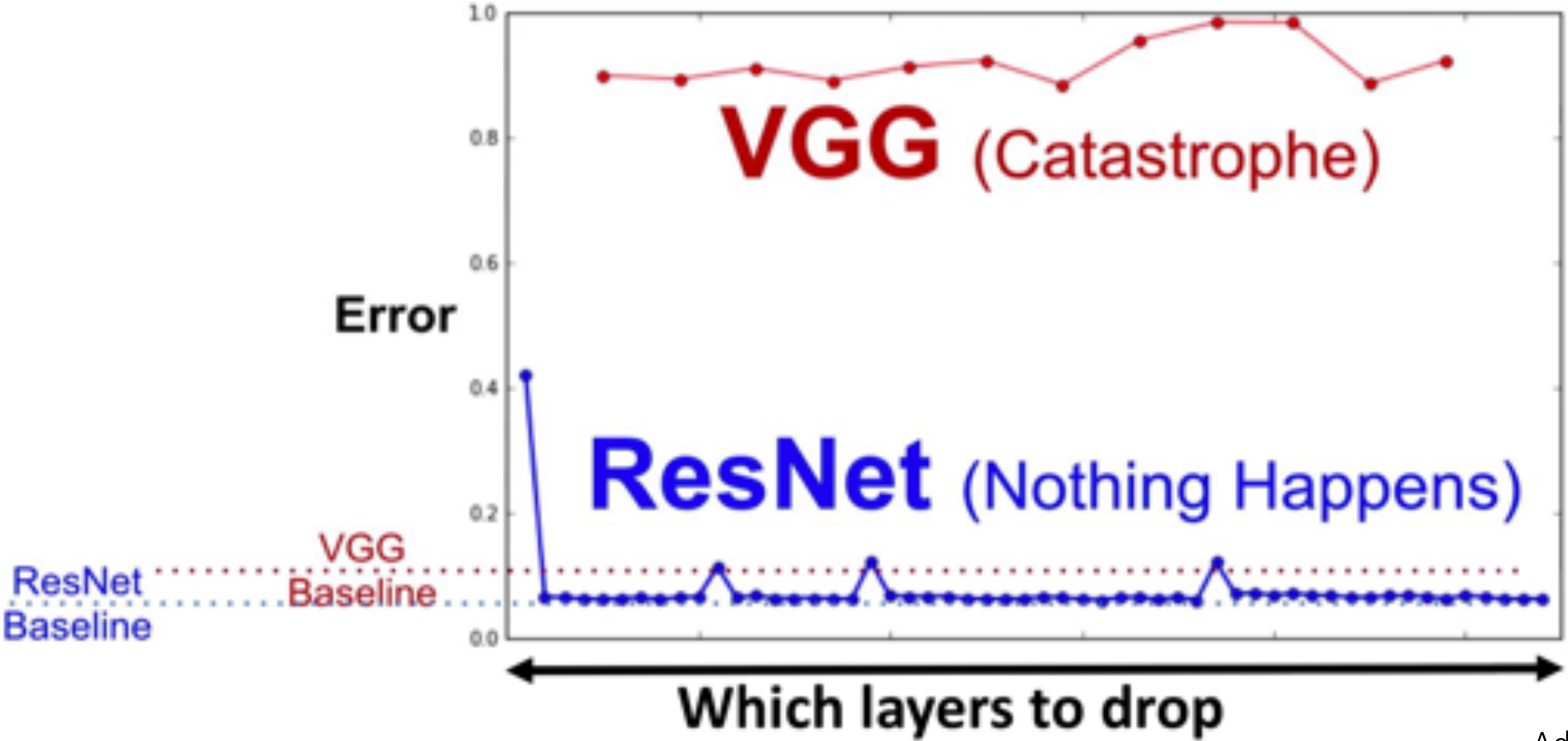
CIFAR-10



Adapted from Veit et al

What happens if we delete a layer at test time?

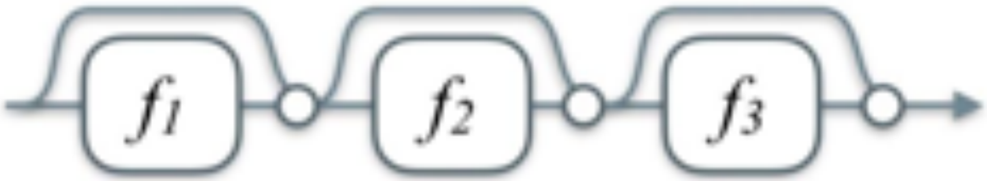
CIFAR-10



Adapted from Veit et al

Why does this happen?

VGG

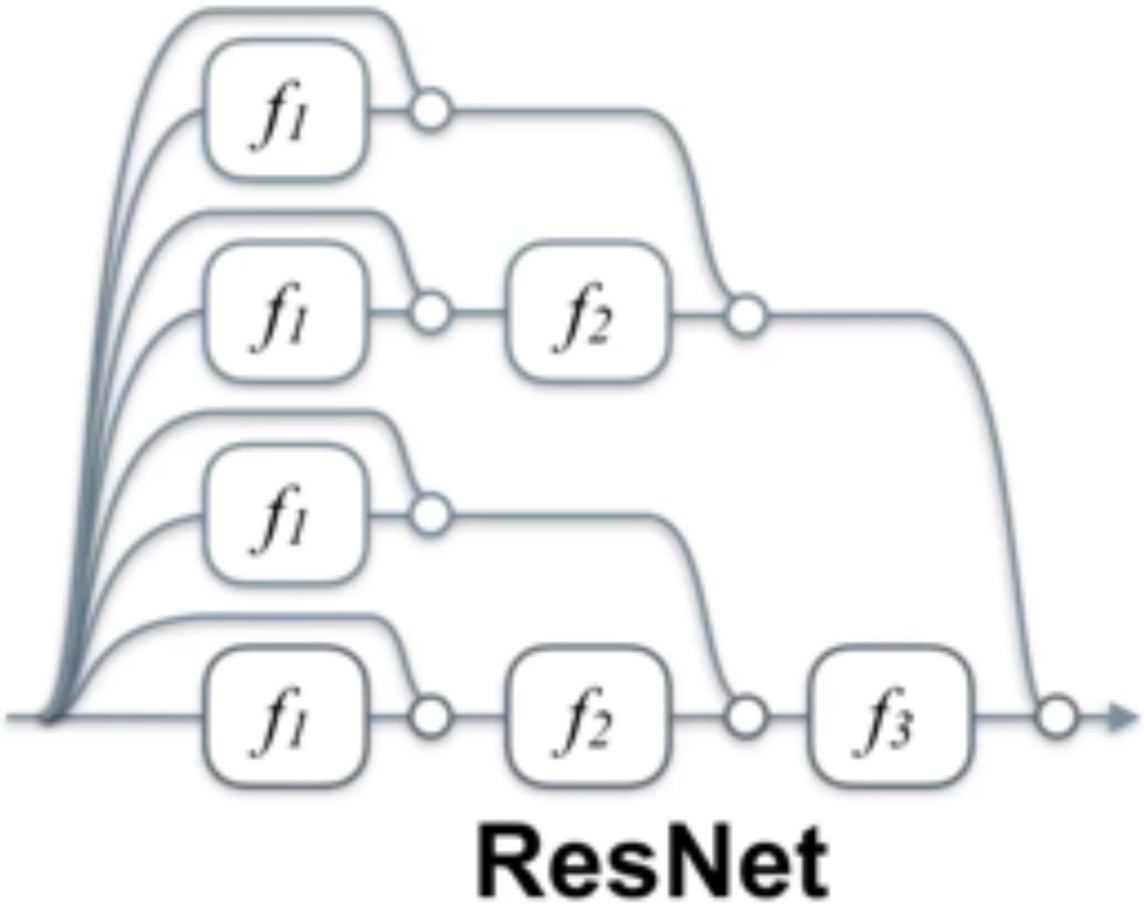


ResNet

Adapted from Veit et al

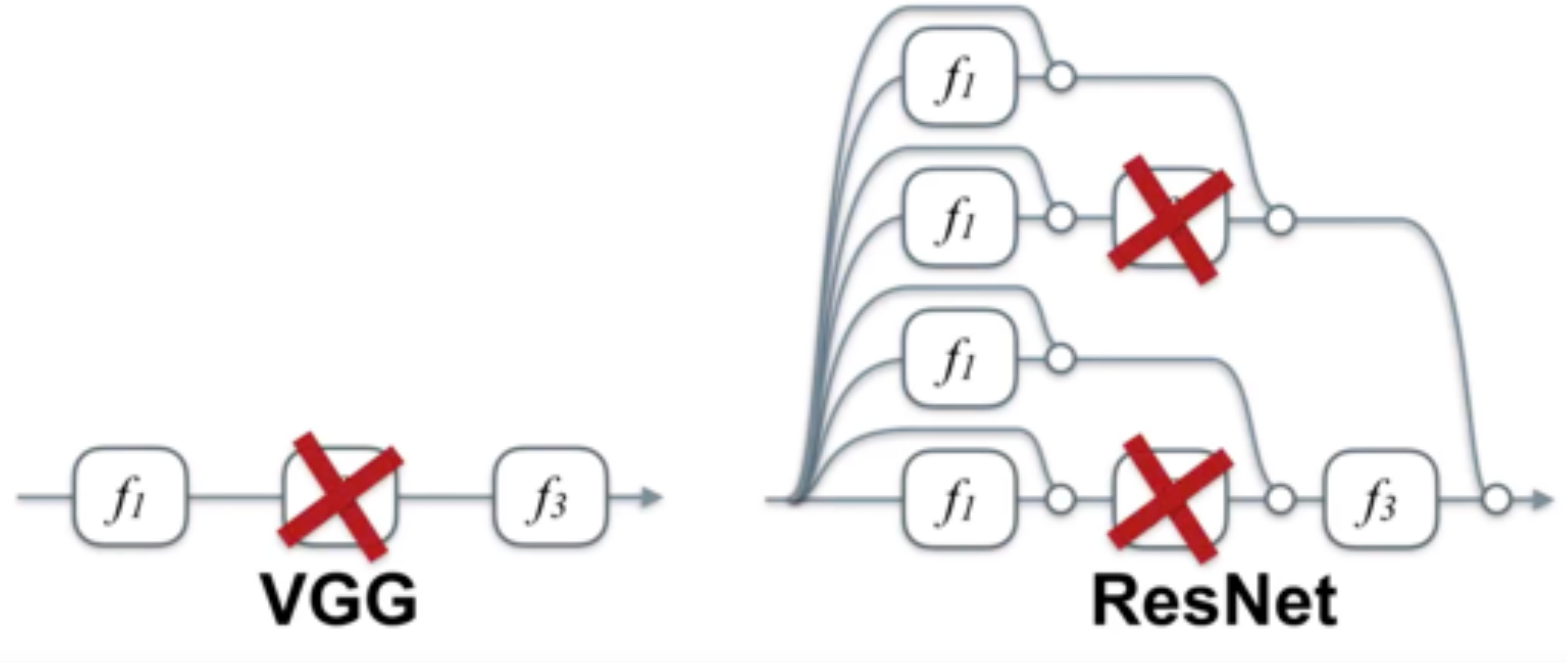
Why does this happen?

The unraveled view is equivalent and showcases the many paths in ResNet.



Adapted from Veit et al

Deletion of a Layer

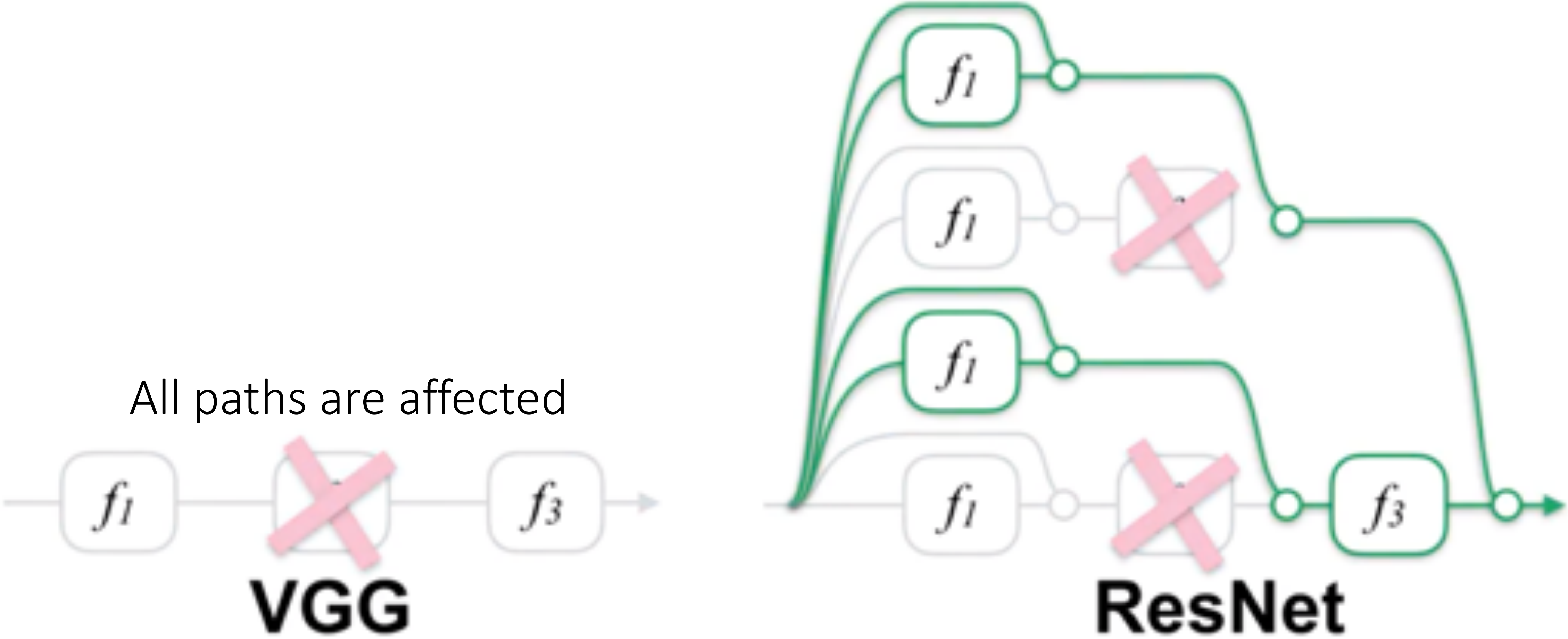


Adapted from Veit et al

Deletion of a Layer

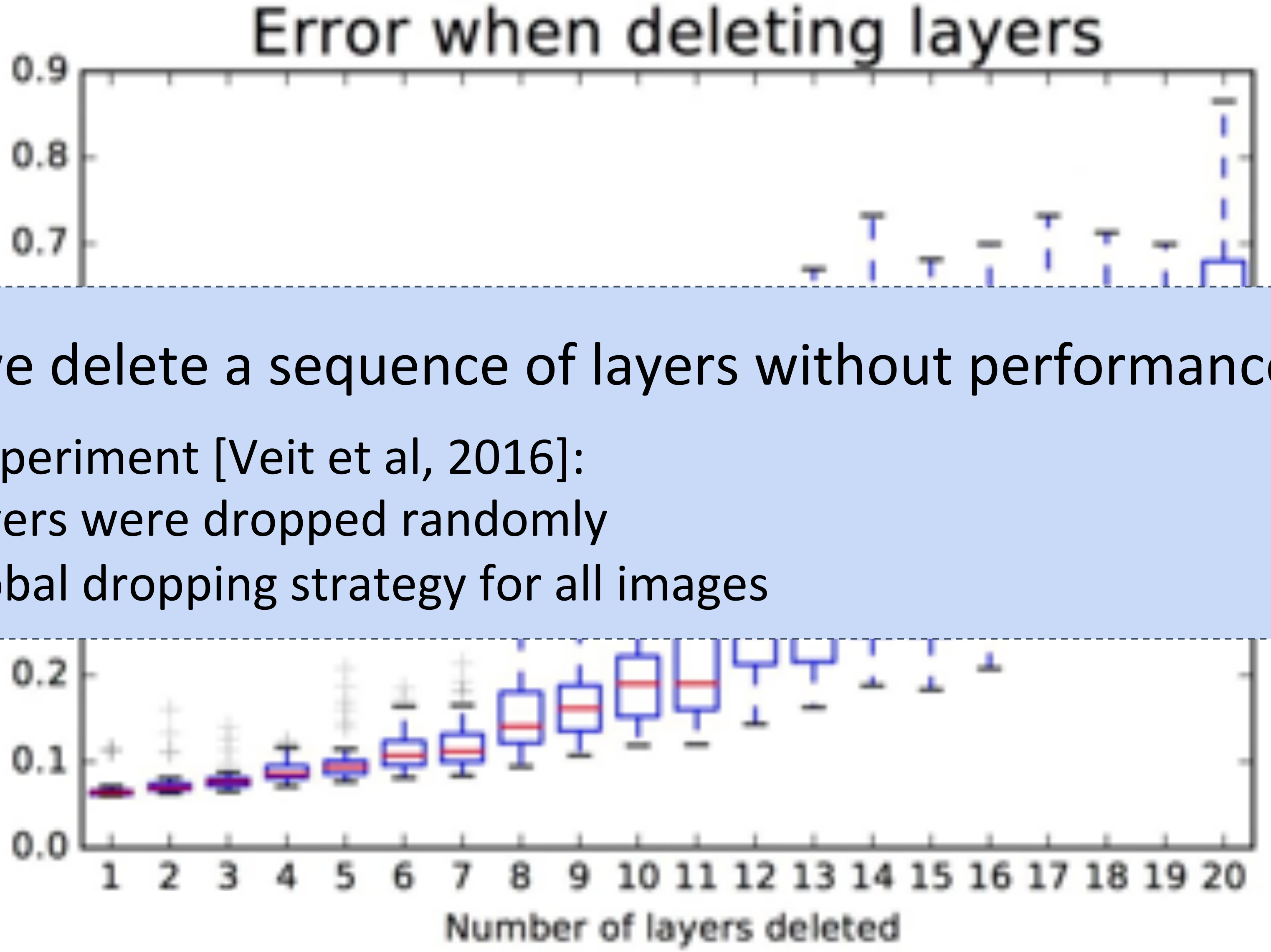
Only half of the paths are affected

All paths are affected



Adapted from Veit et al

Performance varies smoothly when deleting **several** layers.



Can we delete a sequence of layers without performance drop?

This experiment [Veit et al, 2016]:

- Layers were dropped randomly
- Global dropping strategy for all images

Adapted from Veit et al

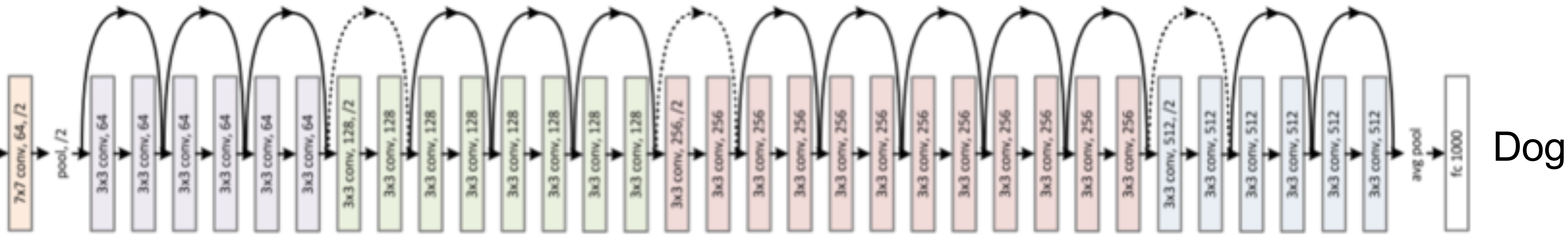
BlockDrop: Dynamic Inference Paths in Residual Networks

Zuxuan Wu*, Tushar Nagarajan*, Abhishek Kumar, Steven Rennie,
Larry S. Davis, Kristen Grauman, Rogerio Feris

CVPR 2018

* Authors contributed equally

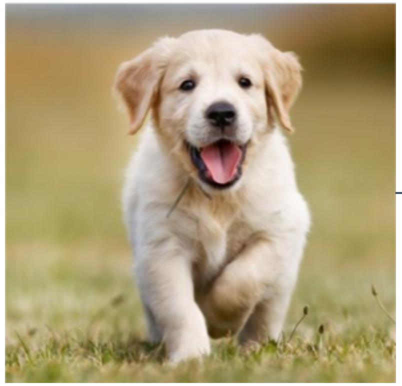
BlockDrop: Dynamic Inference Paths in Residual Networks

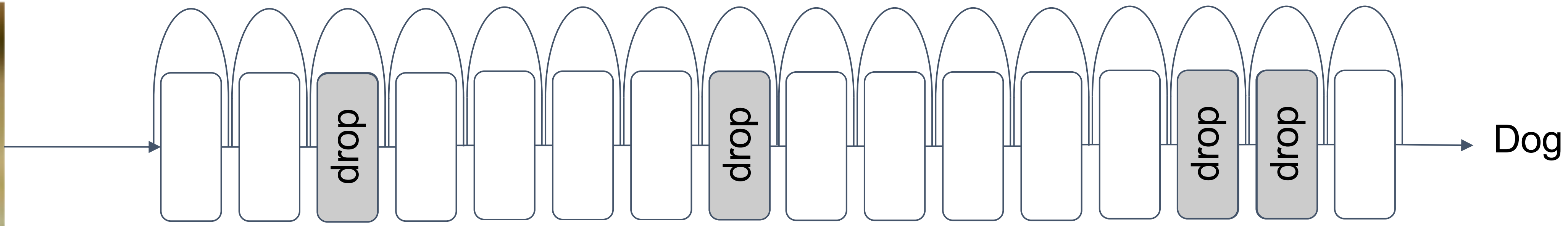


Do we really need to run 100+ layers / residual blocks of a neural network if we have an “easy” input image?

[Wu & Nagarajan et al, CVPR 2018]

BlockDrop: Dynamic Inference Paths in Residual Networks





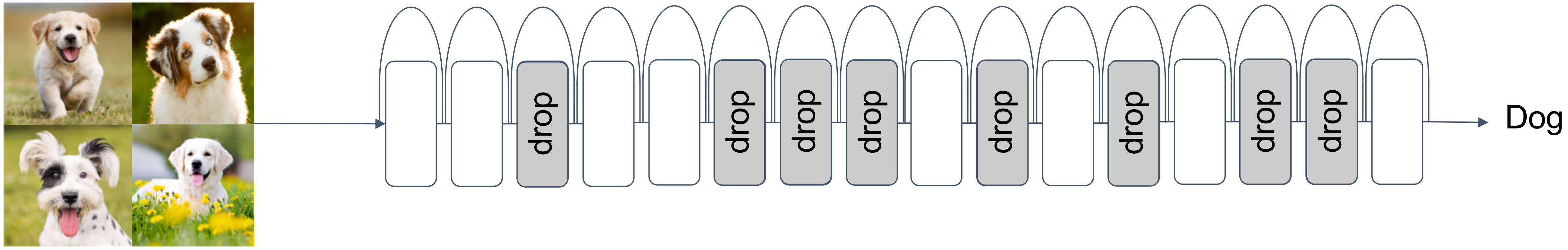
“Dropping some blocks during testing doesn’t hurt performance much”

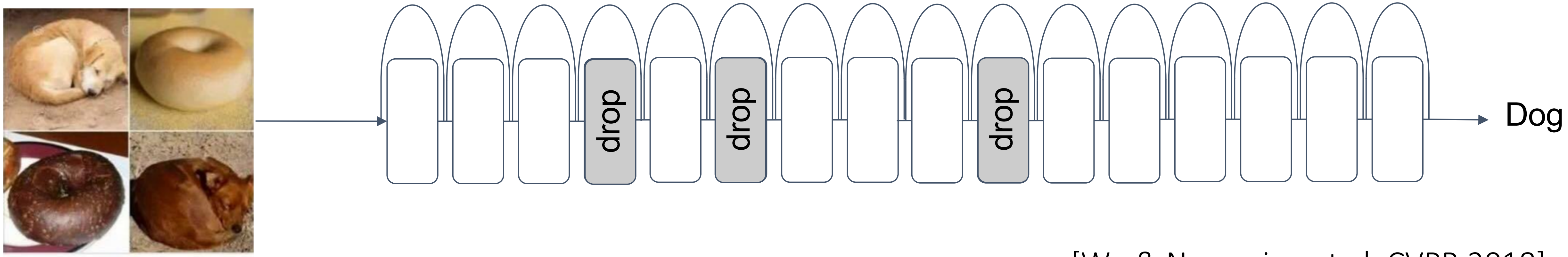
(Veit et al., NIPS 16)

[Wu & Nagarajan et al, CVPR 2018]

BlockDrop: Dynamic Inference Paths in Residual Networks [CVPR 2018]

How to determine which blocks to drop depending on the input image?





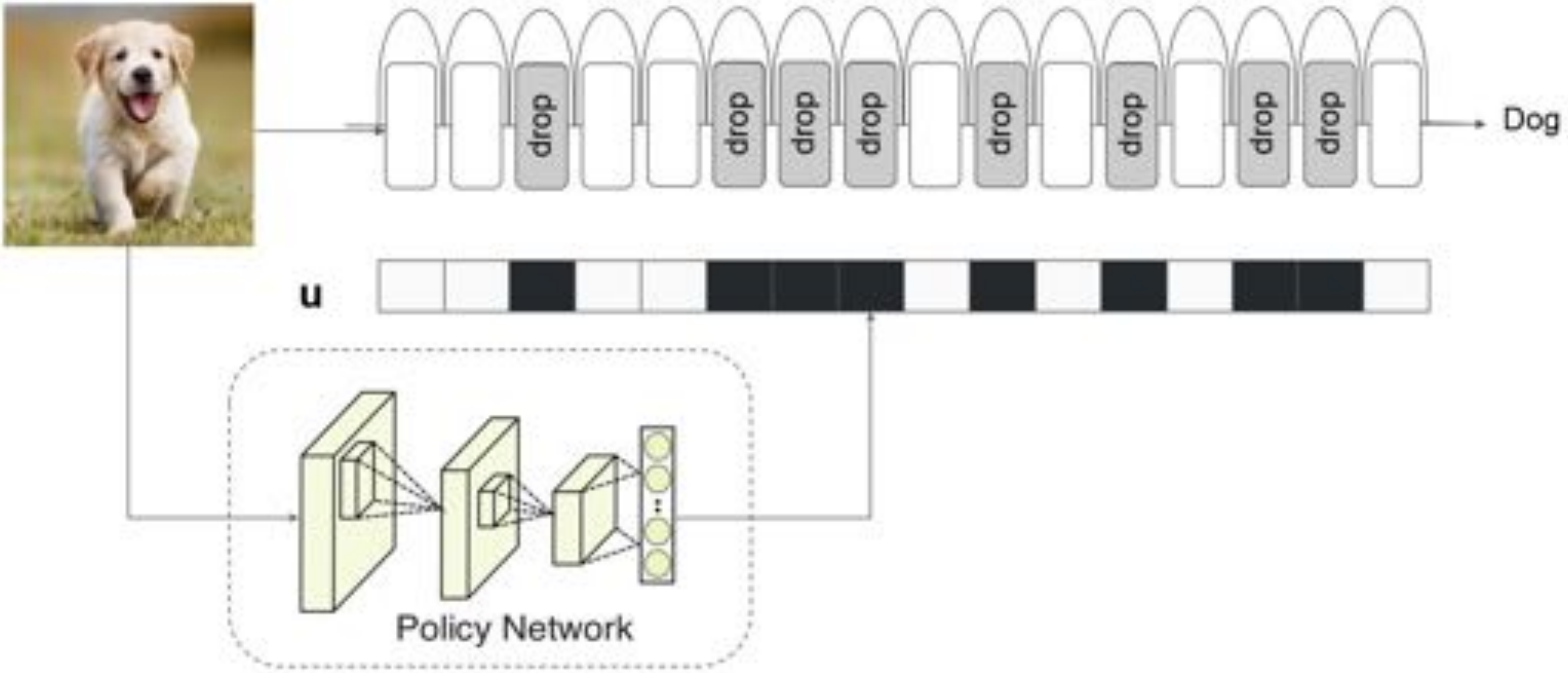
[Wu & Nagarajan et al, CVPR 2018]

Our Idea: BlockDrop

“Predict which blocks to drop conditioned on the input image, in one shot, without compromising accuracy”

[Wu & Nagarajan et al, CVPR 2018]

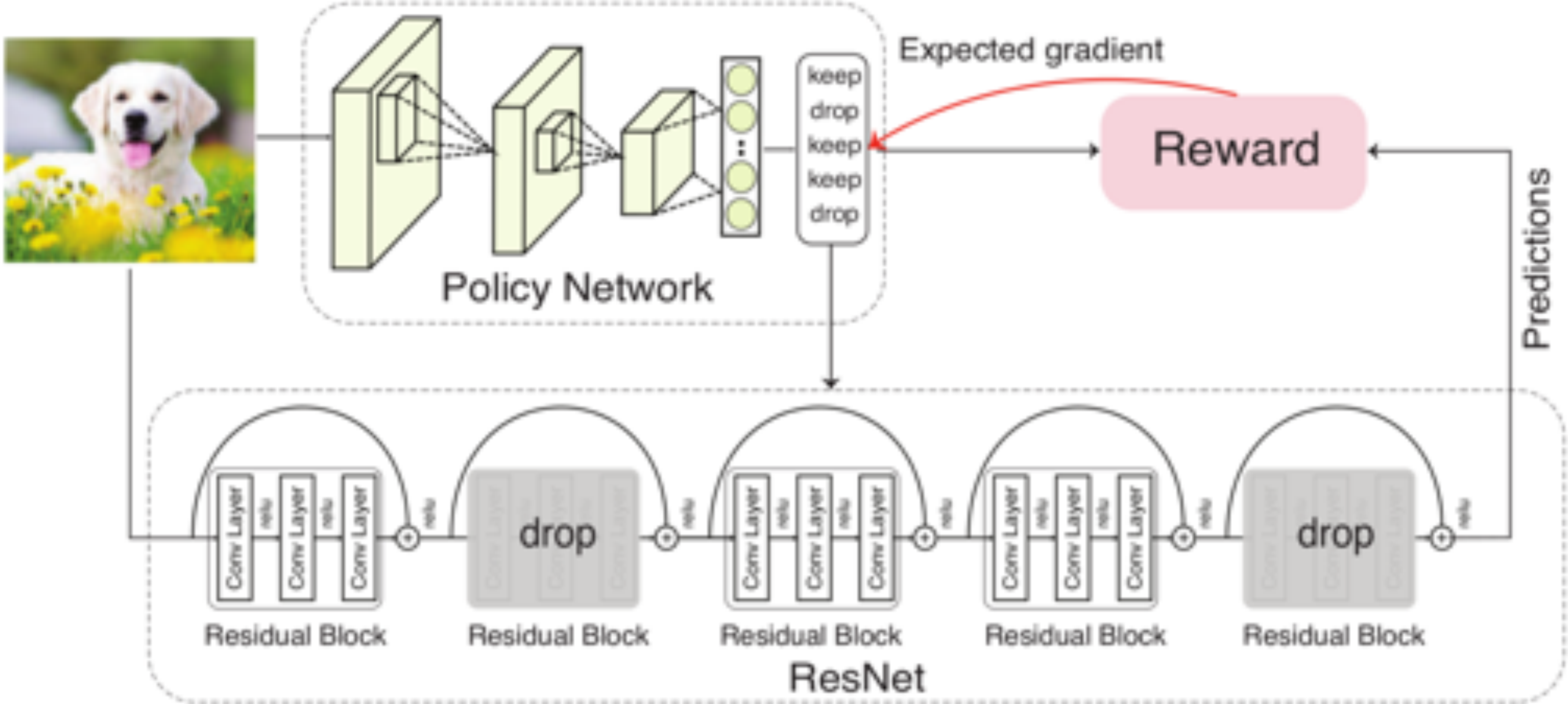
BlockDrop: Dynamic Inference Paths in Residual Networks



[Wu & Nagarajan et al, CVPR 2018]

BlockDrop: Dynamic Inference Paths in Residual Networks [CVPR 2018]

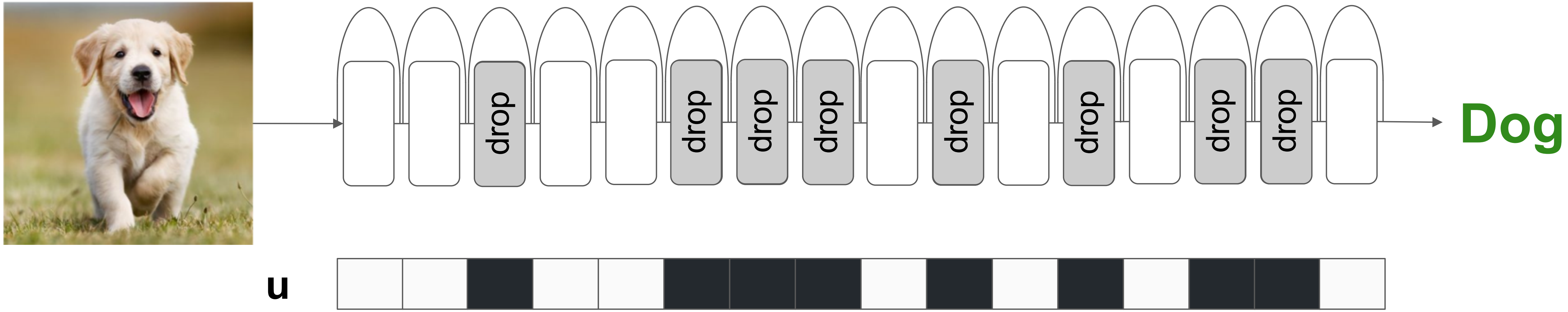
Policy Network Training through Reinforcement Learning



[Wu & Nagarajan et al, CVPR 2018]

BlockDrop: Dynamic Inference Paths in Residual Networks

- Reward function takes into account both accuracy and block usage

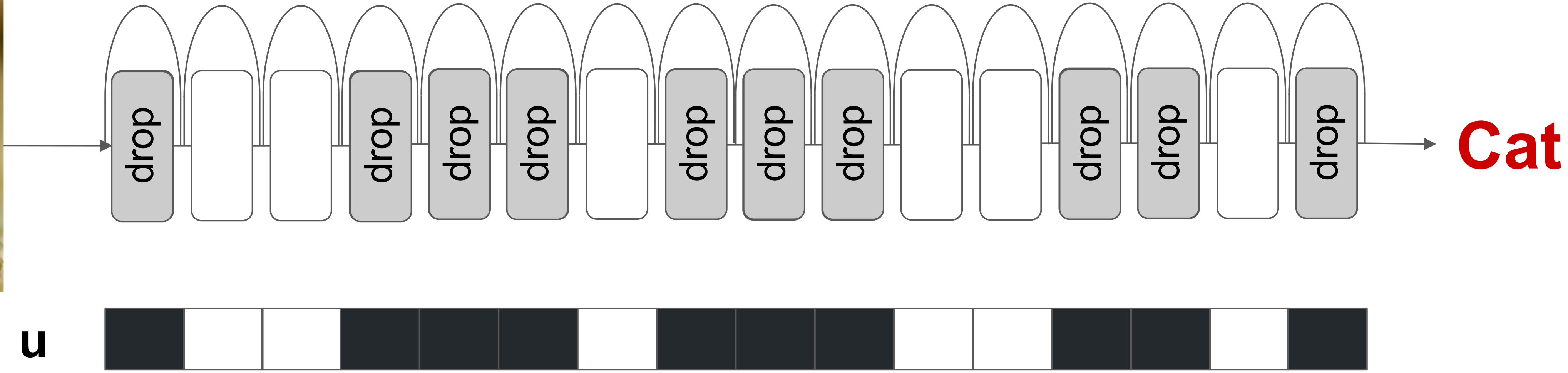


$$R(\mathbf{u}) = \begin{cases} 1 - \left(\frac{|\mathbf{u}|_0}{K}\right)^2 & \text{if correct} \\ -\gamma & \text{otherwise.} \end{cases}$$

$$R(\mathbf{u}) = \mathbf{1} - \left(\frac{\mathbf{8}}{\mathbf{16}}\right)^{\mathbf{2}} = \mathbf{0.75}$$

[Wu & Nagarajan et al, CVPR 2018]

BlockDrop: Dynamic Inference Paths in Residual Networks



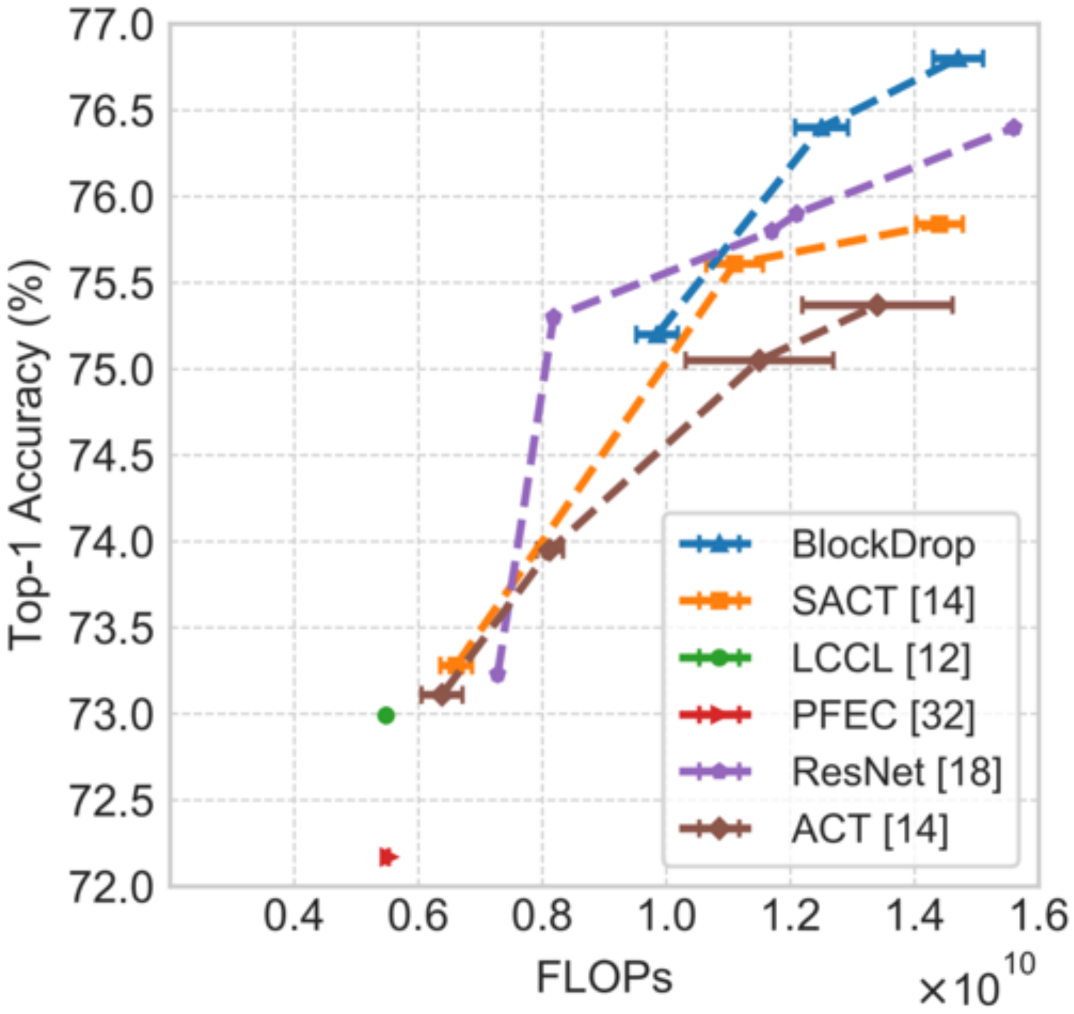
$$R(\mathbf{u}) = \begin{cases} 1 - \left(\frac{|\mathbf{u}|_0}{K}\right)^2 & \text{if correct} \\ -\gamma & \text{otherwise.} \end{cases}$$

$$R(\mathbf{u}) = 1 - \left(\frac{8}{16}\right)^2 = 0.75$$

$$R(\mathbf{u}) = -10$$

[Wu & Nagarajan et al, CVPR 2018]

BlockDrop: Dynamic Inference Paths in Residual Networks



Results on ImageNet:

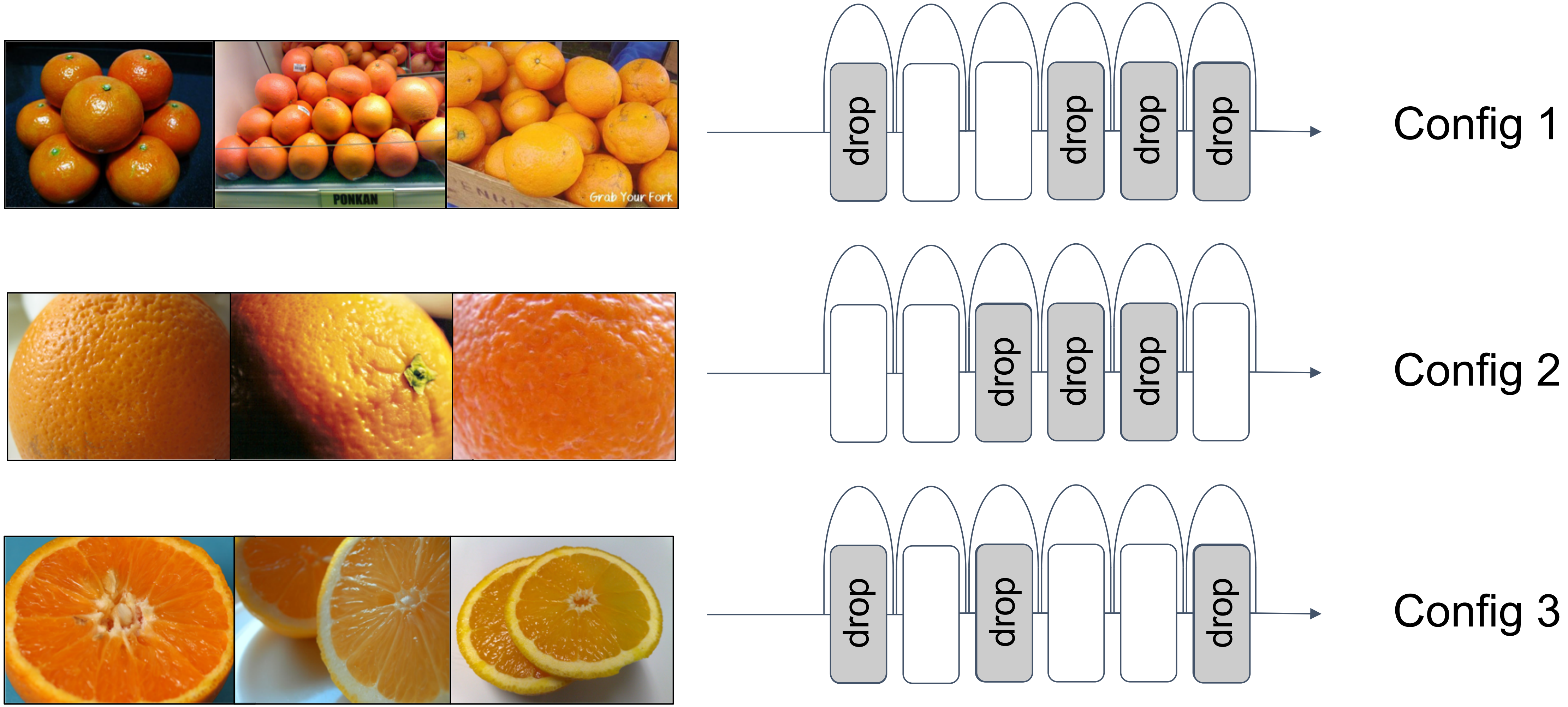
20% - 36% computational savings (FLOPs)

Complementary to other model compression techniques

[Wu & Nagarajan et al, CVPR 2018]

BlockDrop: Dynamic Inference Paths in Residual Networks

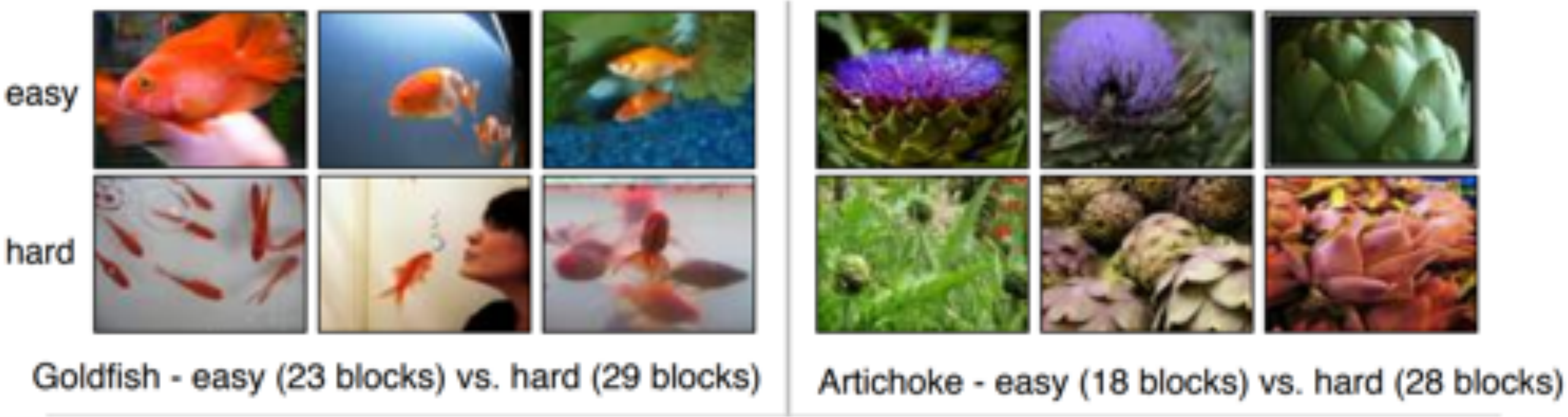
- Different policies capture different visual patterns



orange

[Wu & Nagarajan et al, CVPR 2018]

BlockDrop: Dynamic Inference Paths in Residual Networks



Block usage in neural networks agrees with our perception of *difficulty*

[Wu & Nagarajan et al, CVPR 2018]

SpotTune: Transfer Learning through Adaptive Fine-Tuning

Yunhui Guo, Honghui Shi, Abhishek Kumar, Kristen Grauman,
Tajana Rosing, Rogerio Feris

CVPR 2019

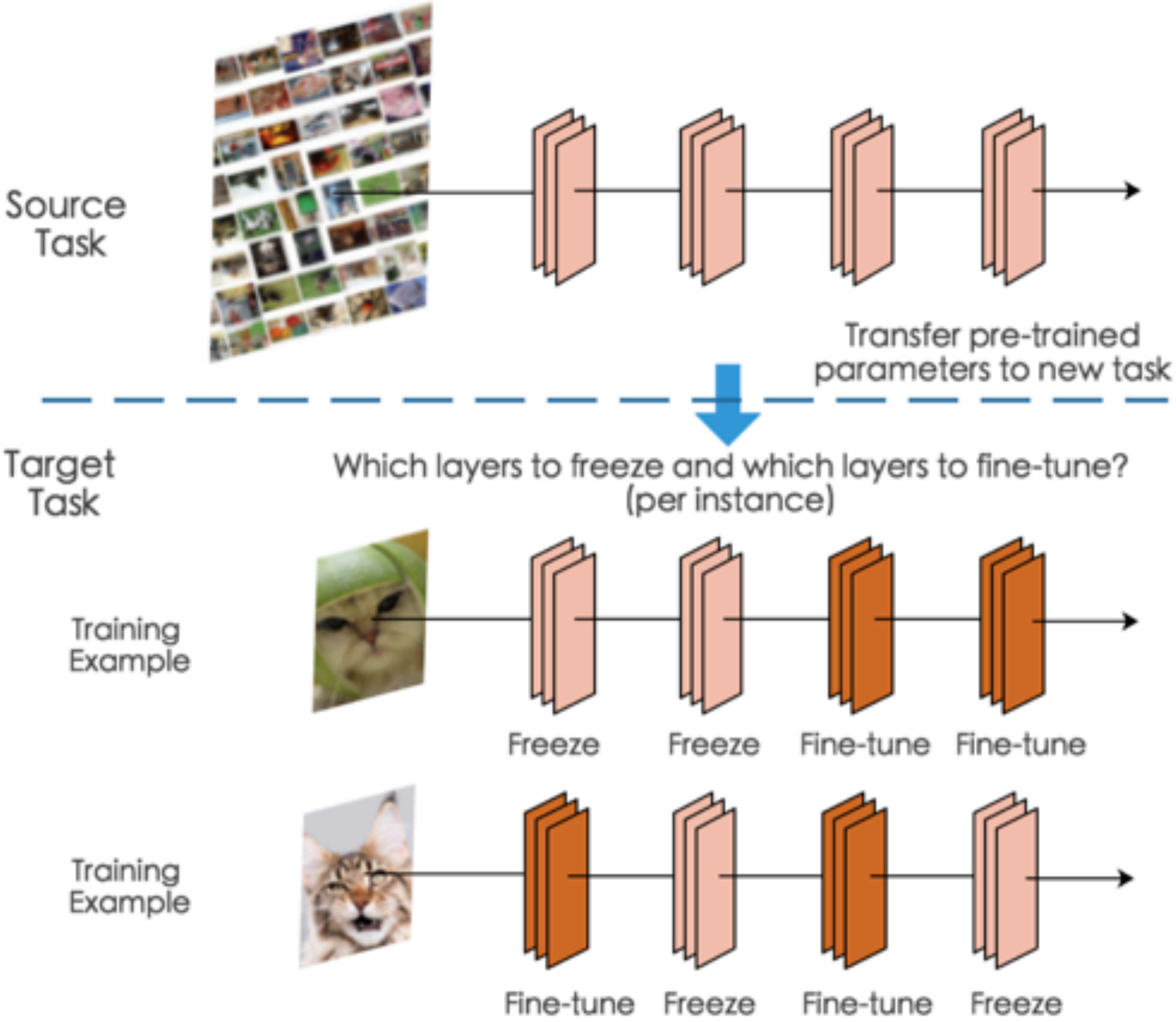
Data Efficiency: Transfer Learning

- Fine-tuning is arguably the most widely used approach for transfer learning

- Existing methods are ad-hoc in terms of determining ***where to fine-tune*** in a deep neural network (*e.g.*, fine-tuning last k layers)

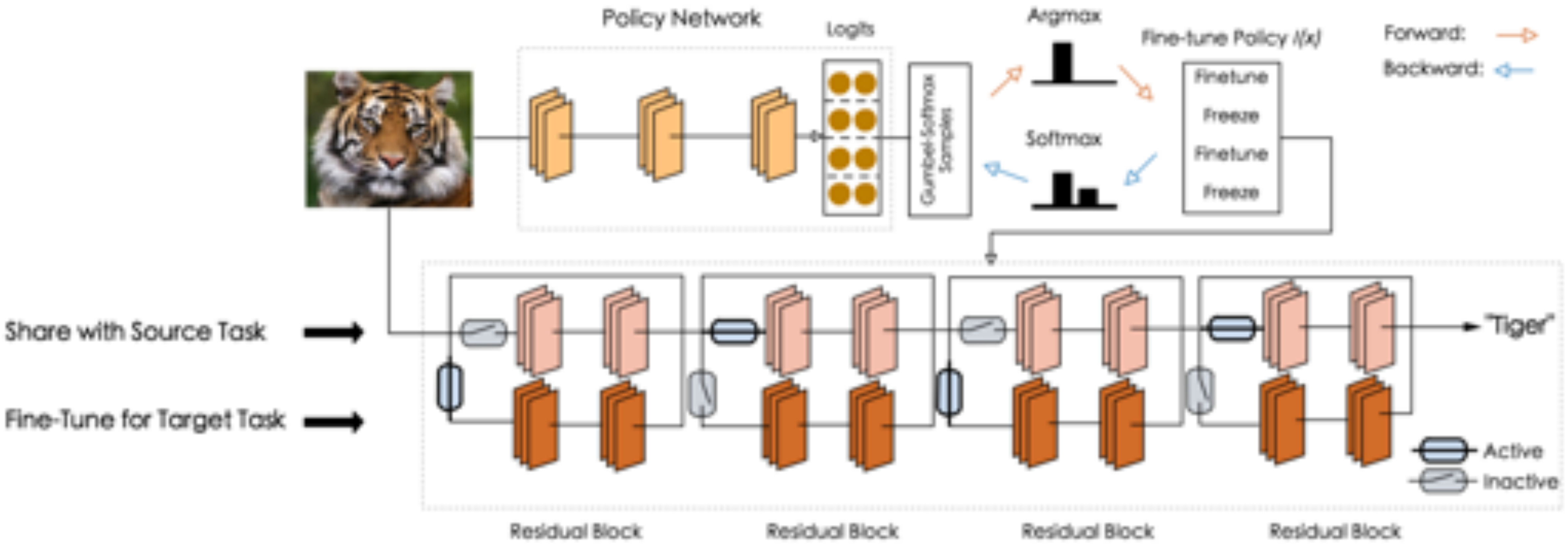
- We propose *SpotTune*, a method that automatically decides, per training example, which layers of a pre-trained model should have their parameters frozen (shared with the source domain) or fine-tuned (adapted to the target domain)

[Guo et al, CVPR 2019]



[Guo et al, CVPR 2019]

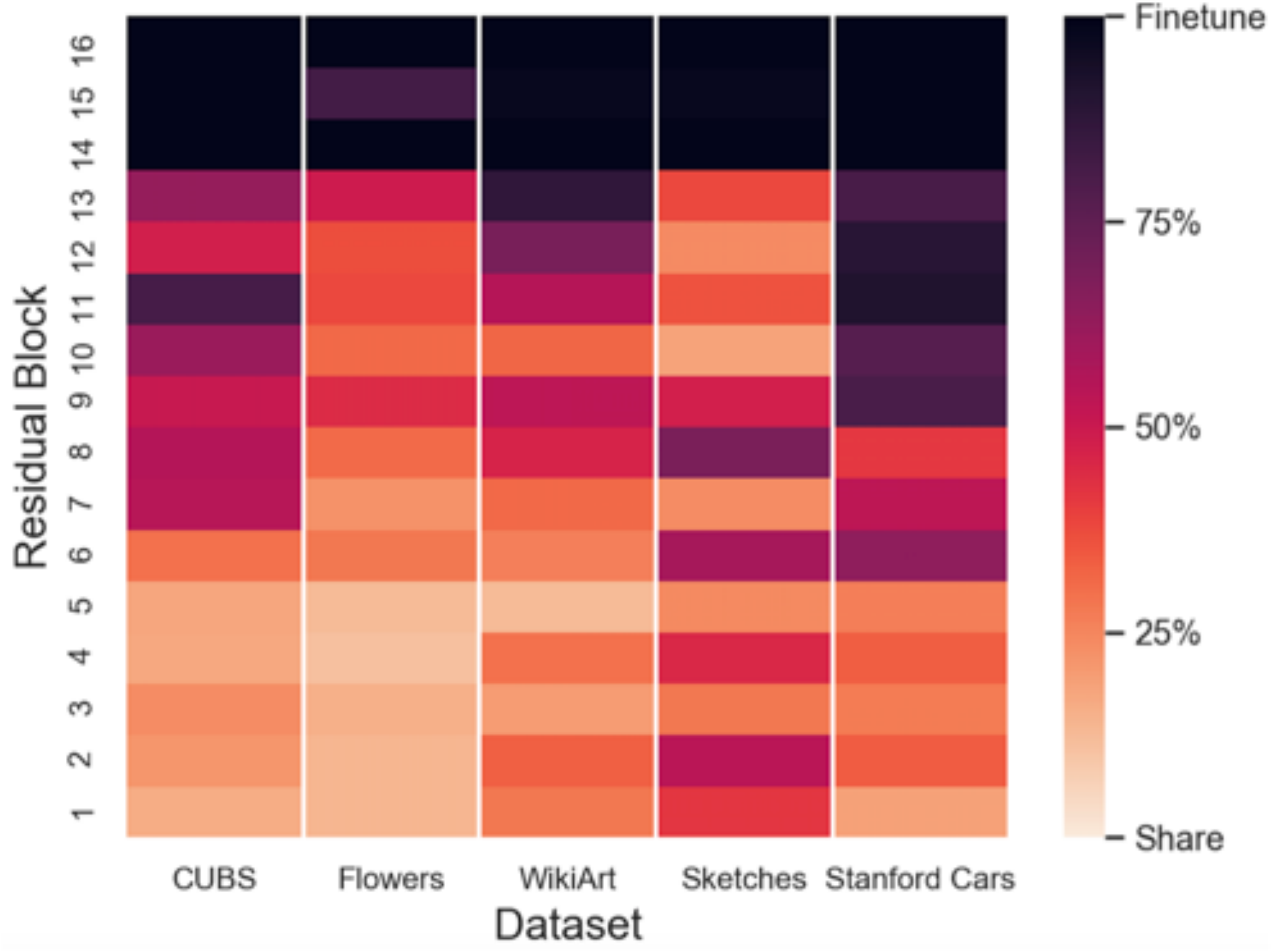
SpotTune: Transfer Learning through Adaptive Fine-Tuning



[Guo et al, CVPR 2019]

SpotTune: Transfer Learning through Adaptive Fine-Tuning

Fine-Tuning Policy Visualization



SpotTune automatically identifies the right fine-tuning policy for each dataset, for each training example.

[Guo et al, CVPR 2019]

SpotTune: Transfer Learning through Adaptive Fine-Tuning

	#par	ImNet	Airc.	C100	DPed	DTD	GTSR	Flwr	OGlt	SVHN	UCF	Score
Scratch	10x	59.87	57.10	75.73	91.20	37.77	96.55	56.30	88.74	96.63	43.27	1625
Scratch+ [37]	11x	59.67	59.59	76.08	92.45	39.63	96.90	56.66	88.74	96.78	44.17	1826
Feature Extractor	1x	59.67	23.31	63.11	80.33	55.53	68.18	73.69	58.79	43.54	26.80	544
Fine-tuning [38]	10x	60.32	61.87	82.12	92.82	55.53	99.42	81.41	89.12	96.55	51.20	3096
BN Adapt. [5]	1x	59.87	43.05	78.62	92.07	51.60	95.82	74.14	84.83	94.10	43.51	1353
LwF [26]	10x	59.87	61.15	82.23	92.34	58.83	97.57	83.05	88.08	96.10	50.04	2515
Series Res. adapt. [37]	2x	60.32	61.87	81.22	93.88	57.13	99.27	81.67	89.62	96.57	50.12	3159
Parallel Res. adapt. [38]	2x	60.32	64.21	81.92	94.73	58.83	99.38	84.68	89.21	96.54	50.94	3412
Res. adapt. (large) [37]	12x	67.00	67.69	84.69	94.28	59.41	97.43	84.86	89.92	96.59	52.39	3131
Res. adapt. decay [37]	2x	59.67	61.87	81.20	93.88	57.13	97.57	81.67	89.62	96.13	50.12	2621
Res. adapt. finetune all [37]	2x	59.23	63.73	81.31	93.30	57.02	97.47	83.43	89.82	96.17	50.28	2643
DAN [39]	2x	57.74	64.12	80.07	91.30	56.54	98.46	86.05	89.67	96.77	49.48	2851
PiggyBack [31]	1.28x	57.69	65.29	79.87	96.99	57.45	97.27	79.09	87.63	97.24	47.48	2838
SpotTune	11x	60.32	63.91	80.48	96.49	57.13	99.52	85.22	88.84	96.72	52.34	**3612**

SpotTune sets the new state of the art on the Visual Decathlon Challenge

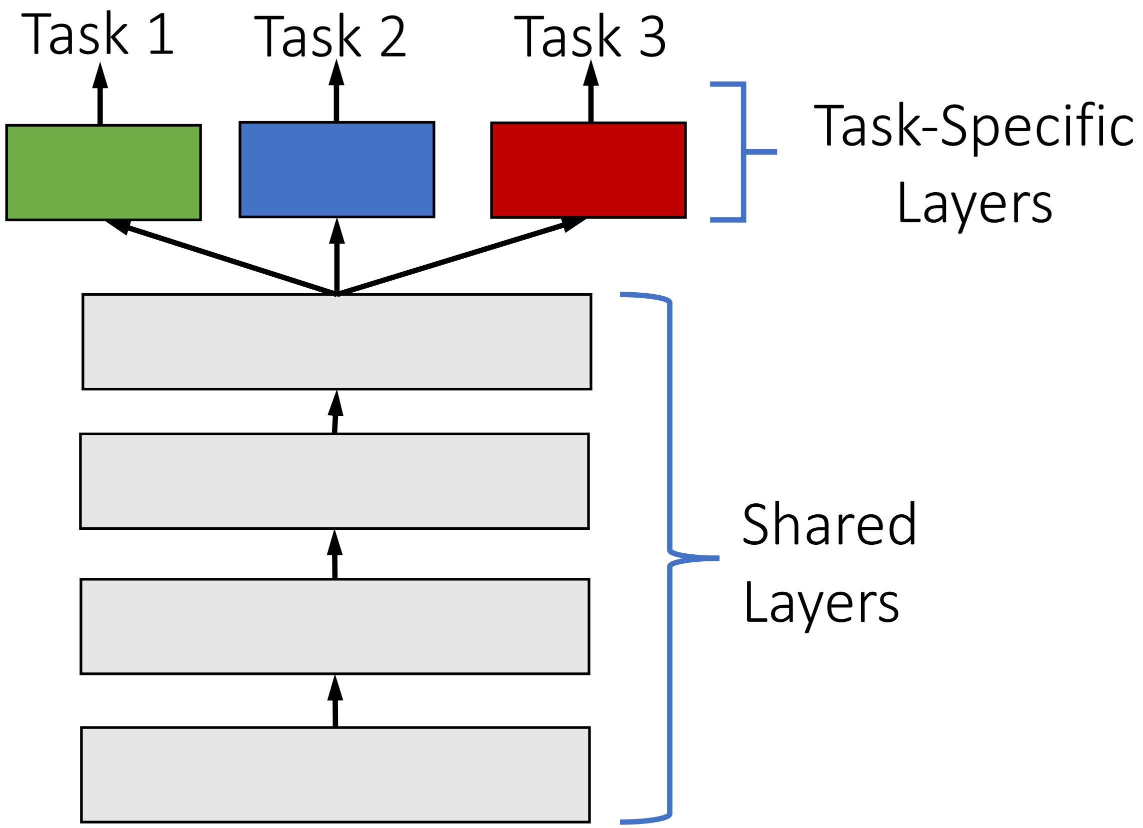
[Guo et al, CVPR 2019]

AdaShare: Learning What to Share for Efficient Multi-Task Learning

Ximeng Sun, Rameswar Panda, Rogerio Feris

Hard Parameter Sharing

- Hand-designed architectures composed of base layers that are shared across tasks and specialized branches that learn task-specific features.

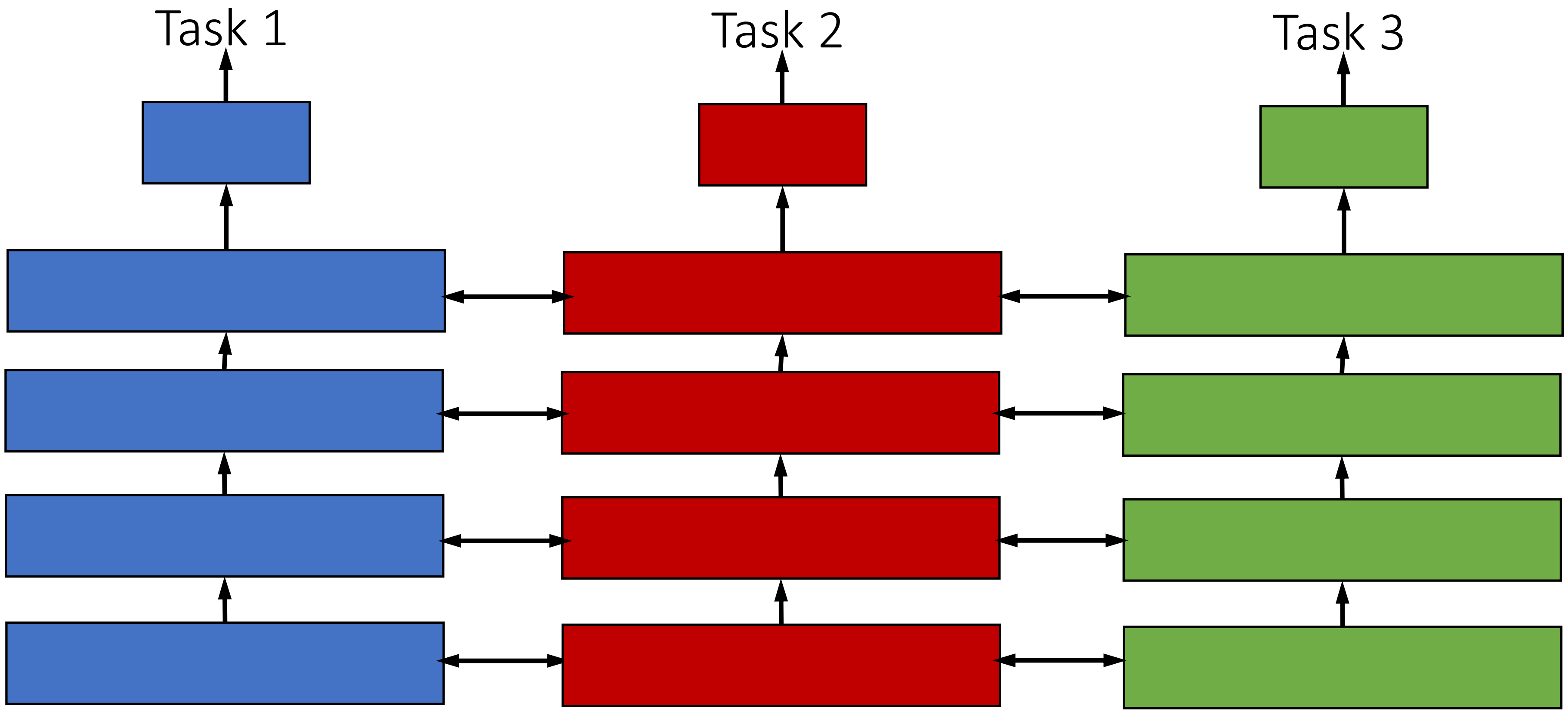


- Performance depends on "where to branch" in the network [Misra et al, 2016]
- The space of possible branching architectures is combinatorially large !

Soft Parameter Sharing

- Network column for each task and a mechanism for feature sharing between columns.

Number of parameters grow linearly with the number of tasks !

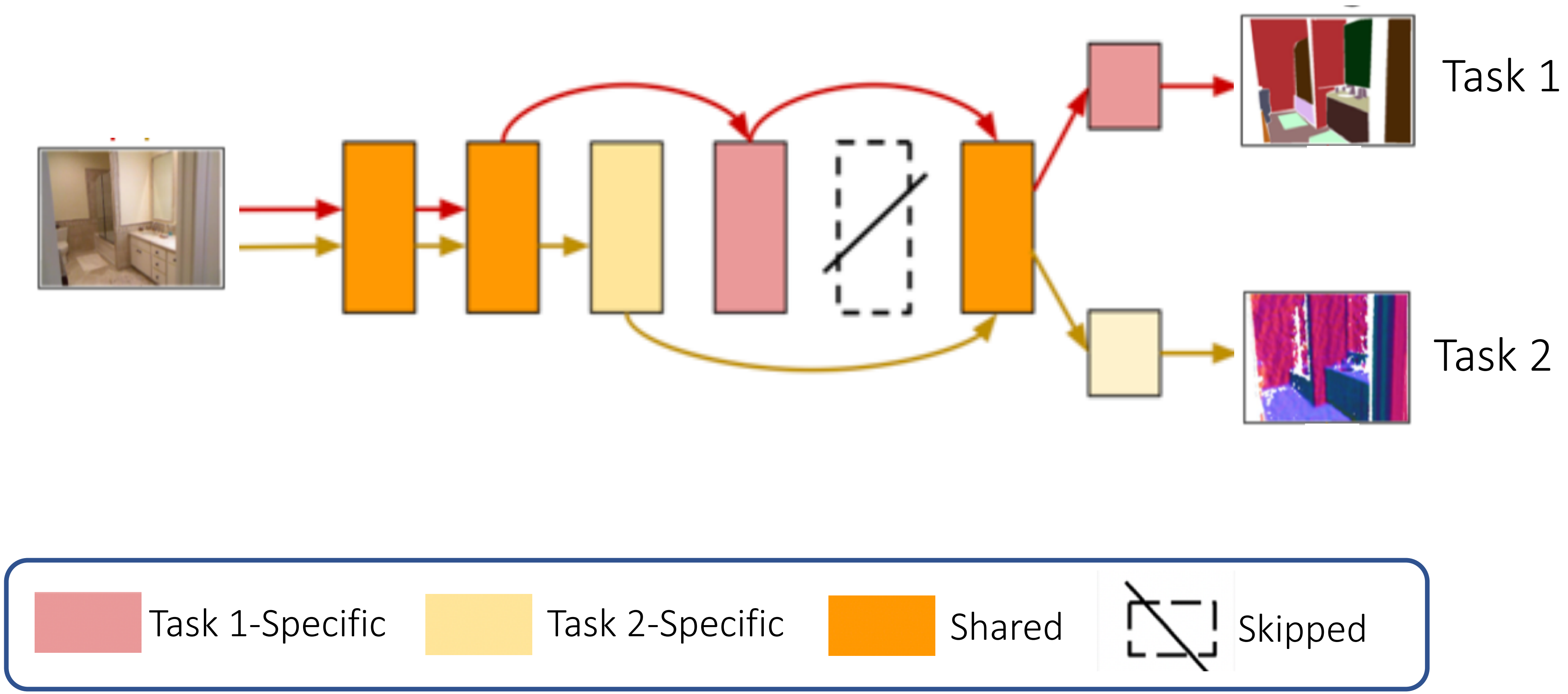


Problem

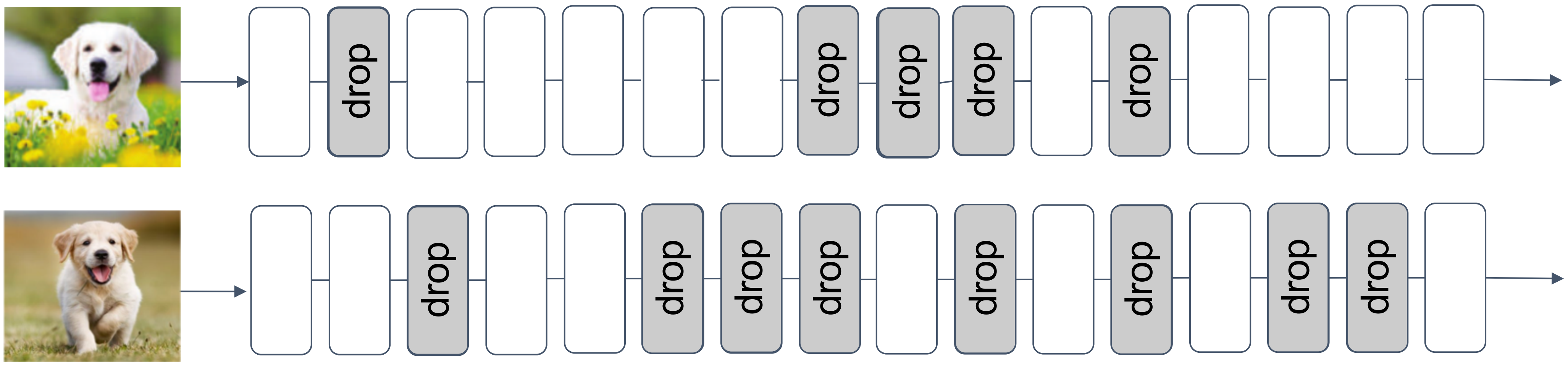
Can we determine which layers in the network should be shared across which tasks and which layers should be task-specific to achieve the best accuracy/memory footprint trade-off for scalable and efficient multi-task learning?

Proposed Approach: AdaShare

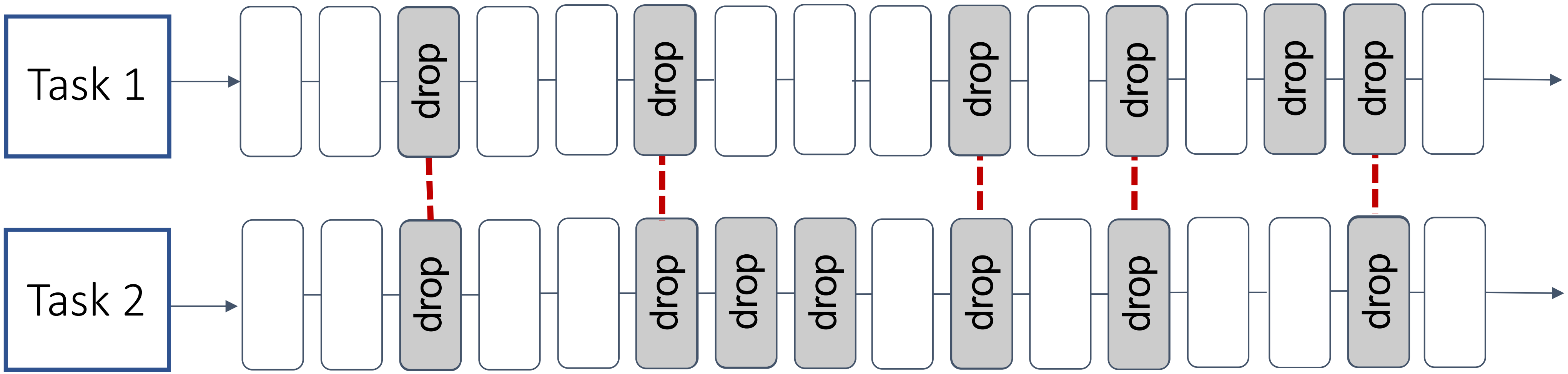
- Single network that supports separate execution paths for different tasks



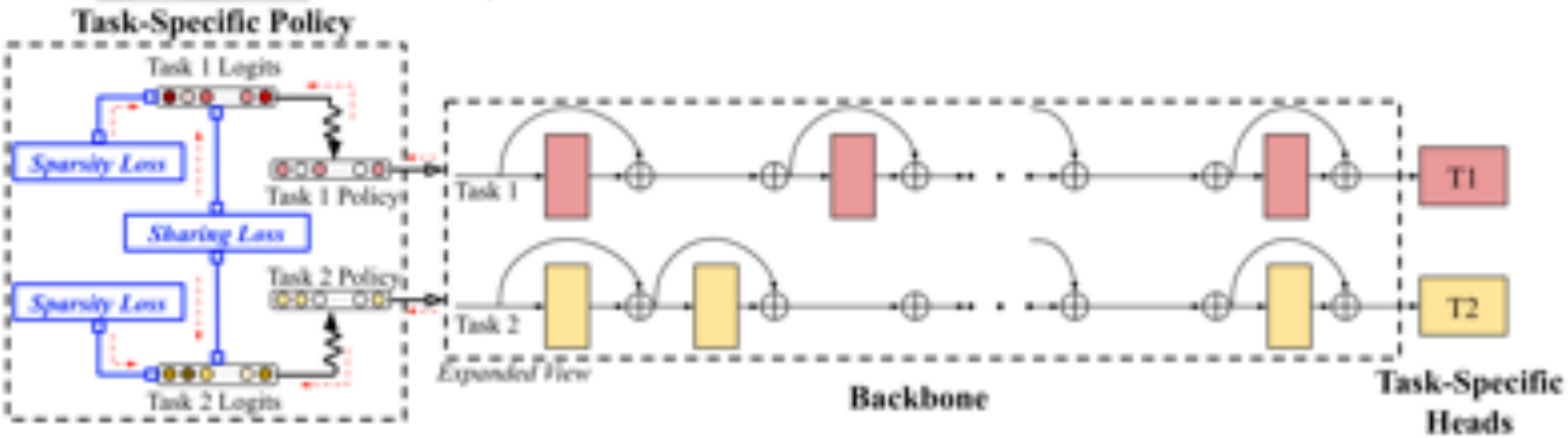
BlockDrop: Per-instance routing; Accuracy + Sparsity reward



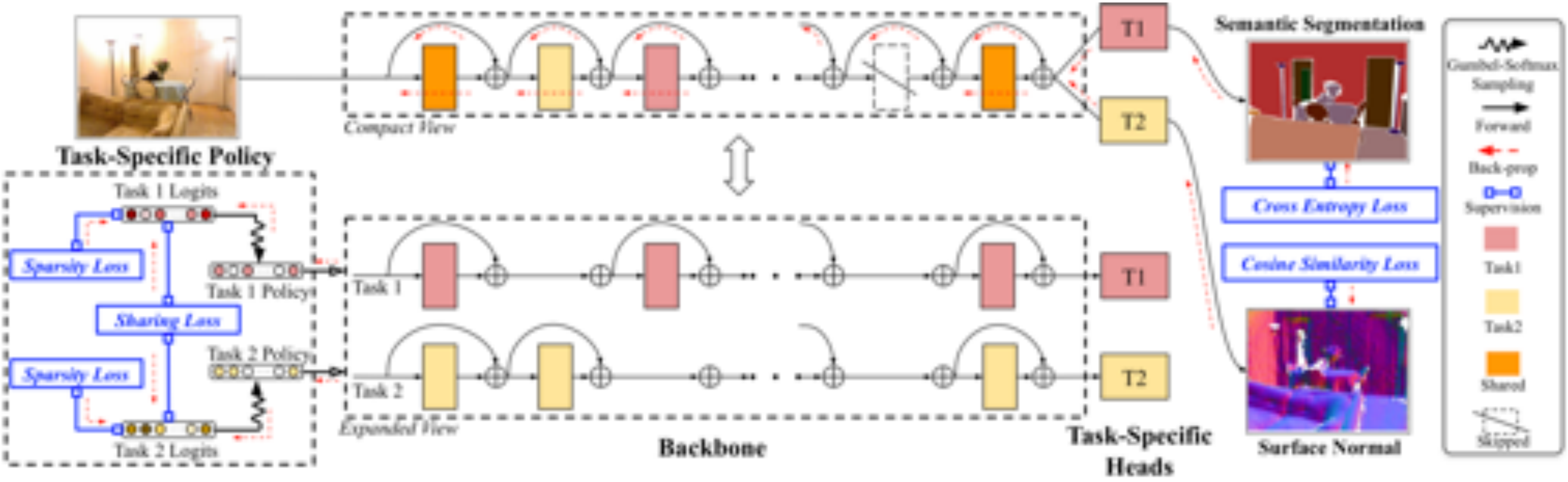
AdaShare: Per-task routing; Accuracy + Sparsity + Sharing reward



AdaShare: Learning what to Share in Multi-Task Learning



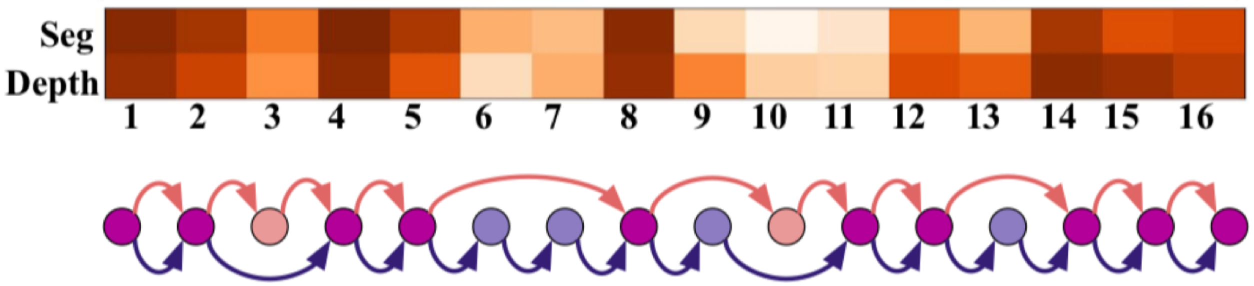
AdaShare: Learning what to Share in Multi-Task Learning



AdaShare: Experimental Results

- **CityScapes [2 tasks].** *AdaShare* achieves the best performance on 5 out of 7 metrics using less than 1/2 parameters of most baselines.

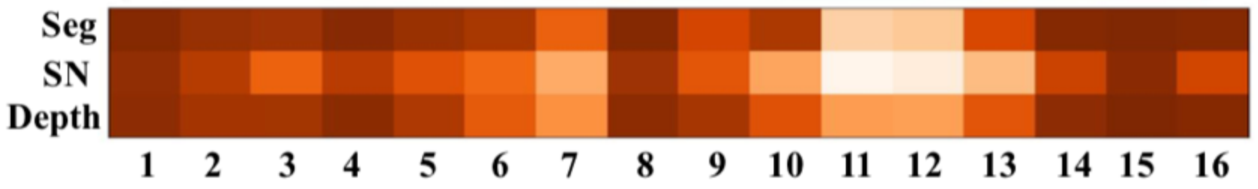
Model	# Params ↓	Semantic Seg.		Depth Prediction				
		mIoU ↑	Pixel Acc ↑	Error↓		δ, within ↑		
				Abs	Rel	1.25	1.25^2	1.25^3
Single-Task	2	40.2	74.7	0.017	0.33	70.3	86.3	93.3
Multi-Task	**1**	37.7	73.8	0.018	0.34	72.4	88.3	94.2
Cross-Stitch	2	40.3	74.3	**0.015**	**0.30**	74.2	89.3	**94.9**
Sluice	2	39.8	74.2	0.016	0.31	73.0	88.8	94.6
NDDR-CNN	2.07	**41.5**	74.2	0.017	0.31	74.0	89.3	94.8
MTAN	2.41	40.8	74.3	**0.015**	0.32	75.1	89.3	94.6
AdaShare	**1**	**41.5**	**74.9**	0.016	0.33	**75.5**	**89.8**	**94.9**

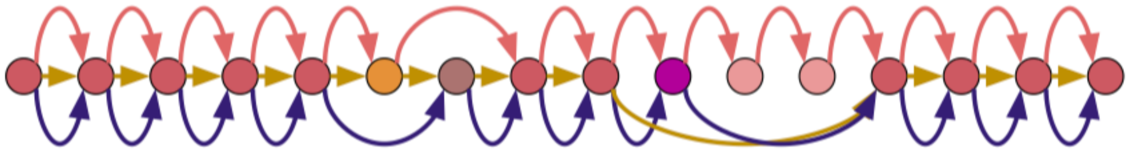


AdaShare: Experimental Results

- **NYU v2 [3 tasks].** AdaShare achieves the best performance on 10 out of 12 metrics using less than 1/3 parameters of most baselines.

Model	# Params ↓	Semantic Seg.		Surface Normal Prediction					Depth Prediction				
				Error ↓		θ, within ↑			Error ↓		δ, within ↑		
		mIoU ↑	Pixel Acc ↑	Mean	Median	11.25°	22.5°	30°	Abs	Rel	1.25	1.25^2	1.25^3
Single-Task	3	27.5	58.9	17.5	15.2	34.9	73.3	85.7	0.62	0.25	57.9	85.8	95.7
Multi-Task	**1**	24.1	57.2	**16.6**	13.4	42.5	73.2	84.6	0.58	0.23	62.4	88.2	96.5
Cross-Stitch	3	25.4	57.6	17.2	14.0	41.4	70.5	82.9	0.58	0.23	61.4	88.4	95.5
Sluice	3	23.8	56.9	17.2	14.4	38.9	71.8	83.9	0.58	0.24	61.9	88.1	96.3
NDDR-CNN	3.15	21.6	53.9	17.1	14.5	37.4	**73.7**	**85.6**	0.66	0.26	55.7	83.7	94.8
MTAN	3.11	26.0	57.2	**16.6**	13.0	43.7	73.3	84.4	0.57	0.25	62.7	87.7	95.9
AdaShare	**1**	**30.2**	**62.4**	**16.6**	**12.9**	**45.0**	71.7	83.0	**0.55**	**0.20**	**64.5**	**90.5**	**97.8**

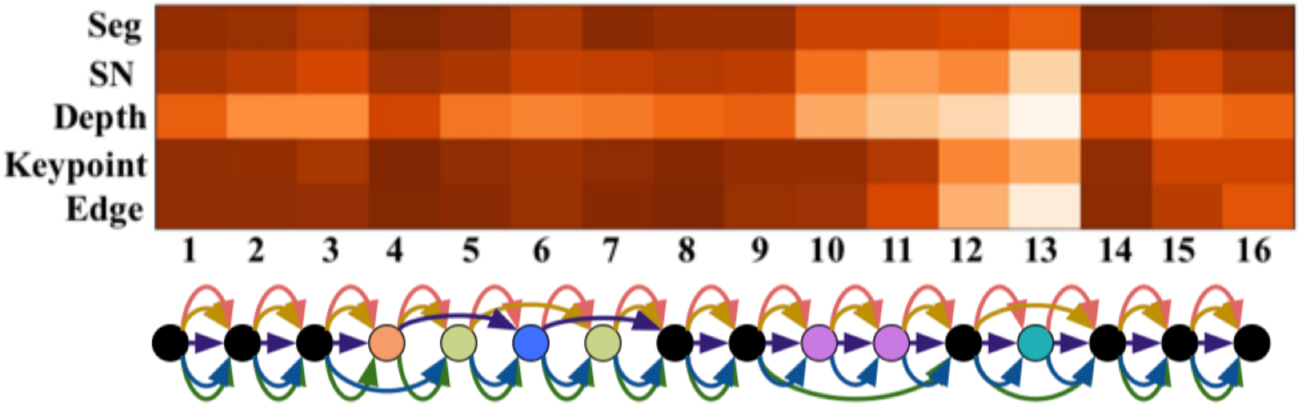




AdaShare: Experimental Results

- **Tiny-Taskonomy [5 Tasks].** AdaShare outperforms the baselines on 3 out of 5 tasks using less than 1/5 parameters of most baselines.

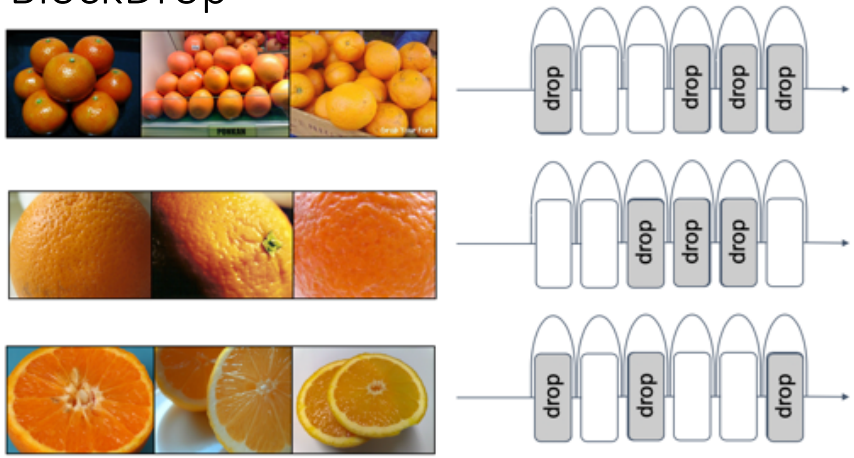
Models	# Params ↓	Seg ↓	SN ↑	Depth ↓	Keypoint ↓	Edge ↓
Single-Task	5	0.575	**0.707**	**0.022**	0.197	0.212
Multi-Task	**1**	0.587	0.702	0.024	0.194	0.201
Cross-Stitch	5	0.560	0.684	**0.022**	0.202	0.219
Sluice	5	0.610	0.702	0.023	**0.192**	0.198
NDDR-CNN	5.41	**0.539**	0.705	0.024	0.194	0.206
MTAN	4.51	0.637	0.702	0.023	0.193	0.203
AdaShare	**1**	0.566	**0.707**	0.025	**0.192**	**0.193**



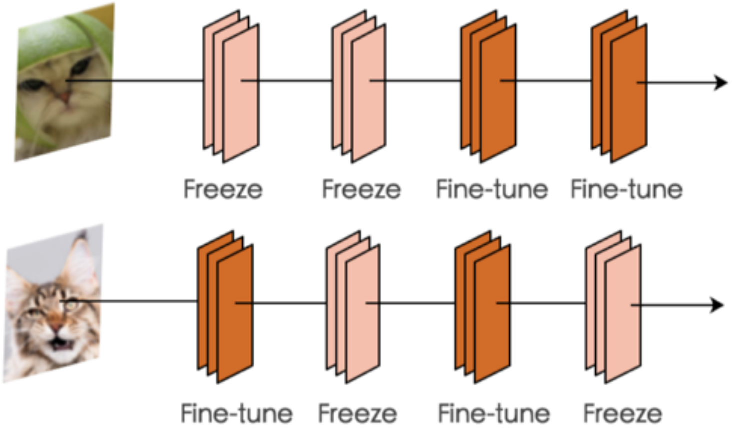
Summary

- Adaptive (dynamic) neural networks for efficient inference

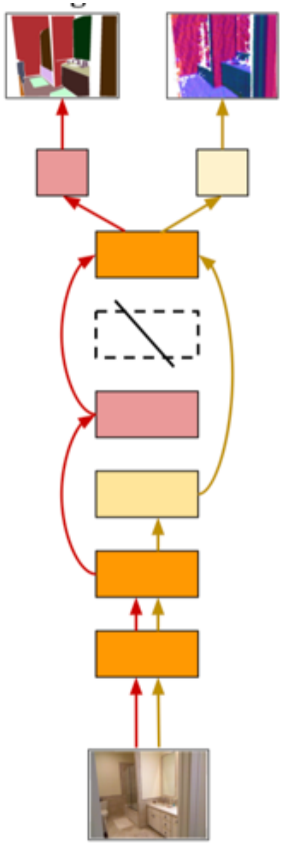
BlockDrop



SpotTune



Adashare



What's Next?

- Adaptive computation for Efficient Multimodal Video Analysis

Thank you !

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- X. Sun, R. Panda and R. S. Feris. “AdaShare: Learning What to Share for Efficient Deep Multi-Task Learning