

A Flexible Selection Scheme for Minimum-Effort Transfer Learning

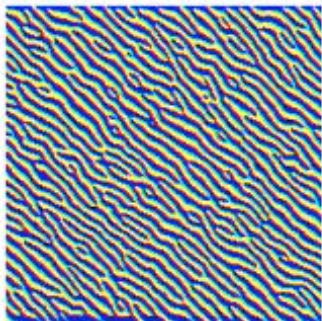
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WACV 2020

Transfer Learning and Fine-tuning

Finetuning: - Pre-trained model on task $T : X \rightarrow Y$
- Retrain last layer(s) for task $T' : X \rightarrow Y'$ with supervision

Hypothesis: Generality of early features for similar datasets

Example: ImageNet classification to Pascal detection



Edges (conv2d0)



Textures (mixed3a)



Patterns (mixed4a)


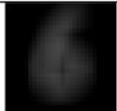











Parts (mixed4b)



Objects (mixed4d)

How to handle visually dissimilar domains ?

Source	Target domains		
 MNIST (subset) [22] 25k images 10 classes 4-layers top-1: 0.989	 Blurry top-1: 0.748	 Occluded top-1: 0.581	 MNIST-M [9] top-1: 0.439
	 Transform (random) top-1: 0.322	 SVHN [26] top-1: 0.211	 Transform (fixed) top-1: 0.160
ratios \sim 3, 30, 300 and 3k images per class			
 CIFAR (subset) [20] 18k images 9 classes 7-layers top-1: 0.738	 Noisy top-1: 0.540	 Blurry top-1: 0.324	 QuickDraw [6] top-1: 0.291
ratios \sim 2, 20, 200 and 2k images per class			

Assumption of similar early features break.

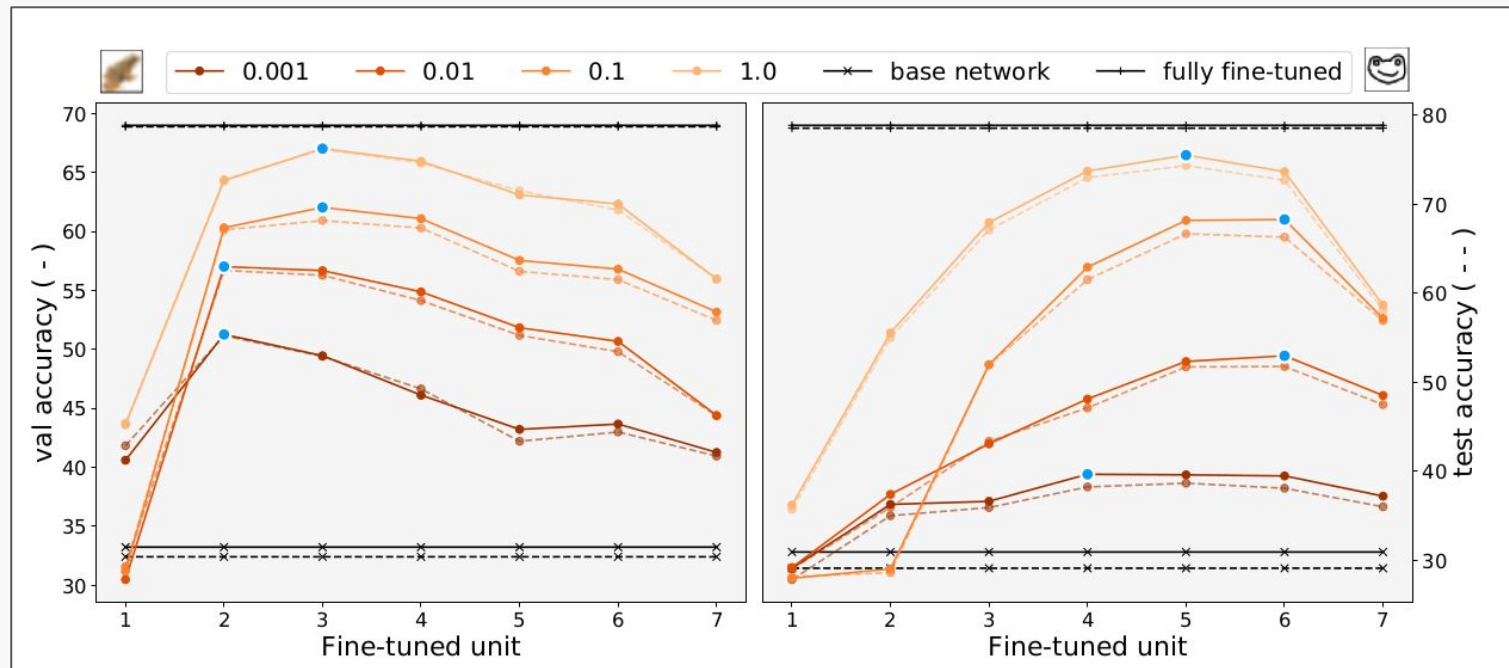
but fine-tuning the whole architecture is not always an option
(e.g., lack of data, risk of overfitting)

Yet, similar semantics (output space)

Can we learn to mend the representation by tuning one intermediate unit (layer or block of layers) in the architecture ?

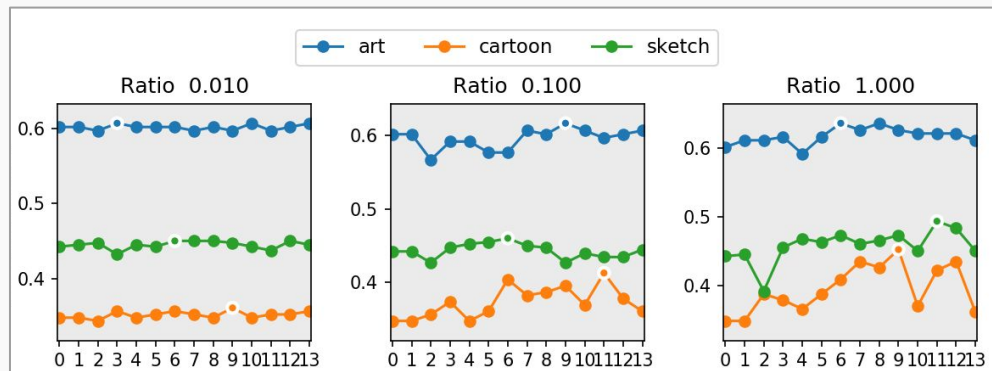
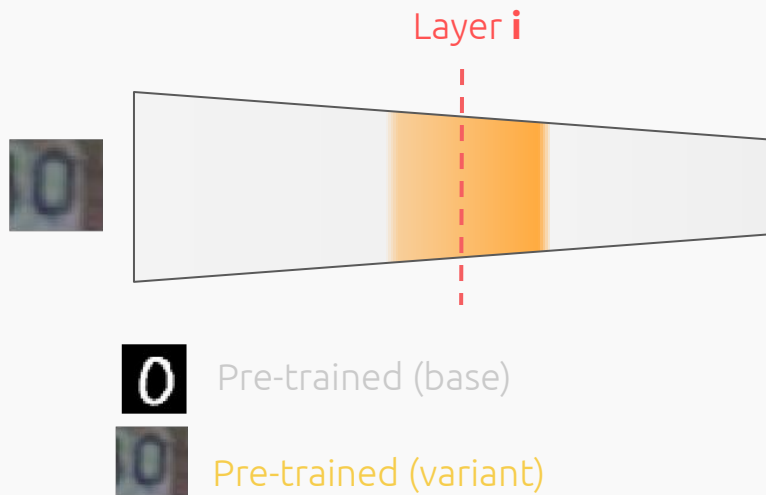
Flextuning: A model selection criterion

Evaluate best unit to tune based on accuracy on the validation set



Flextuning: Faster variants

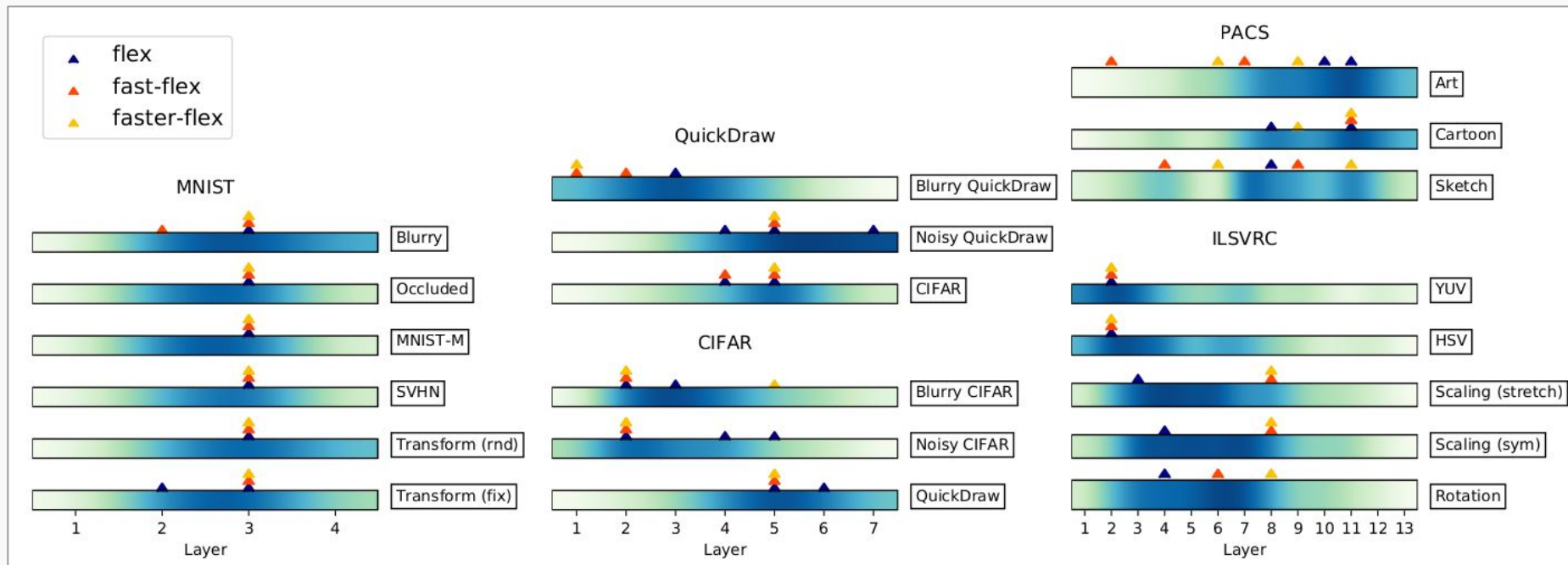
Approximate how each unit will impact the end model accuracy by network “surgery” after several (fast-flex) or one (faster-flex) training epoch



Qualitative results

Agreement across the different criteria

Selection pattern dependent on the domain shift








Quantitative results

Experiments across different visual **domain shifts** and **data scarcity** scenarios.

- On large architectures, less prone to overfitting.

- On local distortions, improved accuracies on the target set by selecting early units

ILSVRC 	flex			ft-		
	flex	fast	faster	fc	ss	all
YUV (0.84) 	0.893	0.893	0.893	0.835	0.699	0.808
HSV (0.38) 	0.856	0.856	0.856	0.533	0.646	0.687
Scaling (stretch) (0.44) 	0.724	0.696	0.696	0.502	0.584	0.653
Scaling (sym.) (0.52) 	0.770	0.757	0.757	0.663	0.650	0.716
Rotation (0.74) 	0.826	0.832	0.812	0.667	0.652	0.771

ILSVRC 	flex			ft-		
	flex	fast	faster	fc	ss	all
ratio: 200 images per class						
Art (0.53) 	0.906	0.906	0.823	0.791	0.887	0.746
Cartoon (0.32) 	0.958	0.956	0.952	0.868	0.956	0.925
Sketch (0.14) 	0.924	0.924	0.890	0.767	0.916	0.875