



MixMo: Mixing Multiple Inputs for Multiple Outputs via Deep Subnetworks

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Machine Learning &
Deep Learning for
Information Access

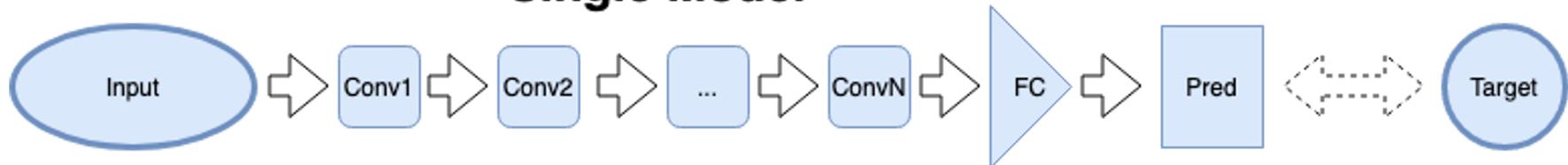
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THALES

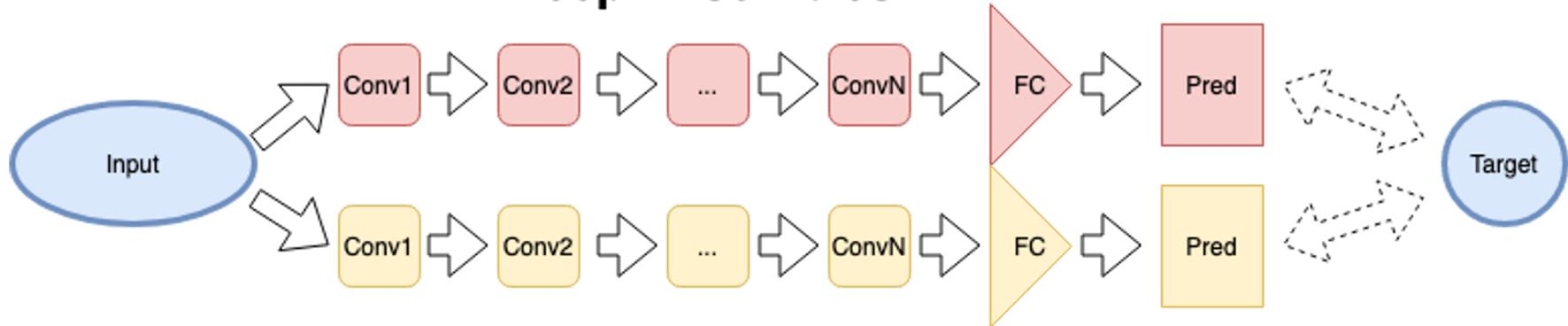


Deep ensembles

Single Model



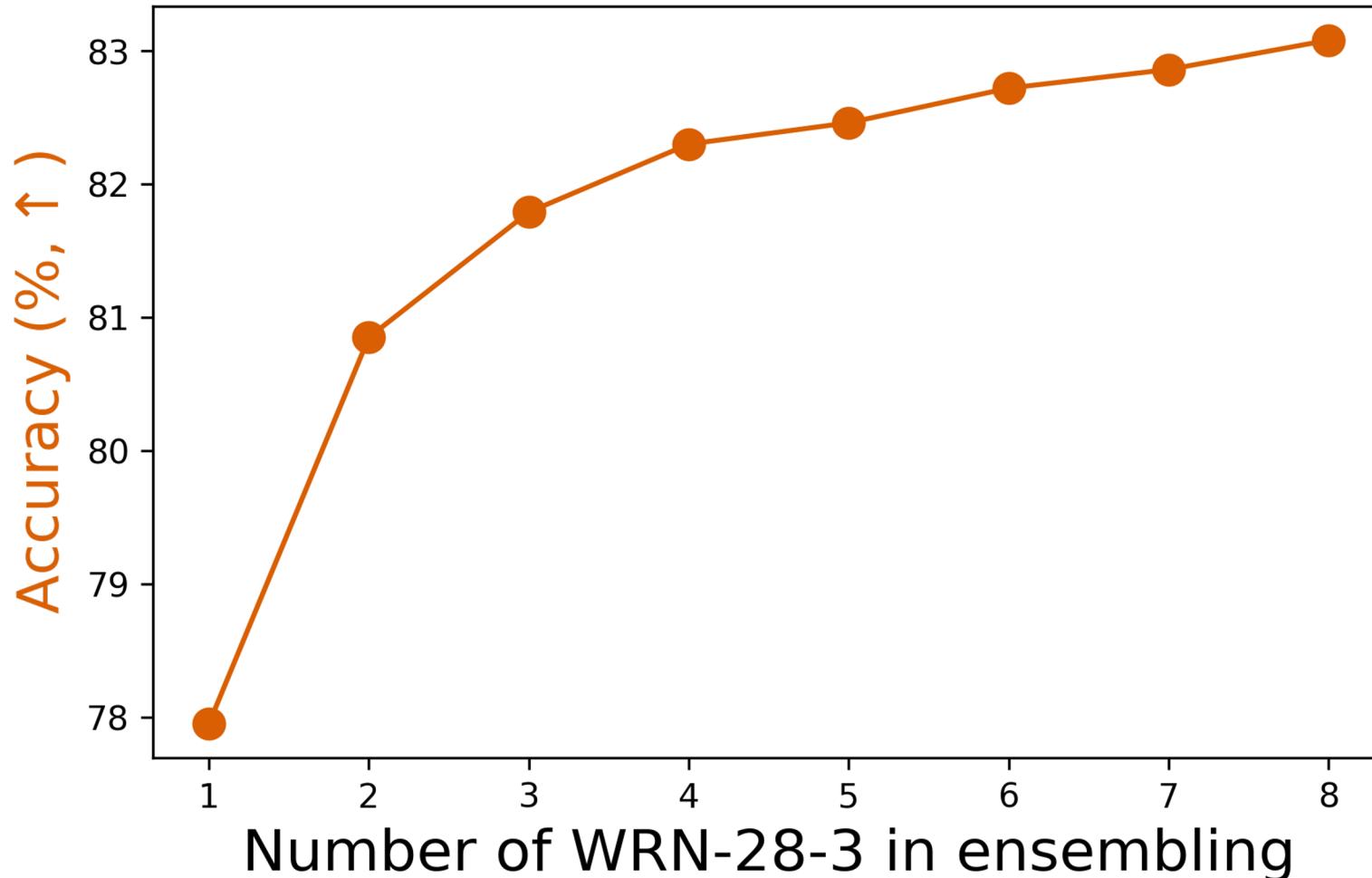
Deep Ensembles



[1] Simple and scalable predictive uncertainty estimation using deep ensembles. Lakshminarayanan *et al.*, in *NeurIPS 2017*.

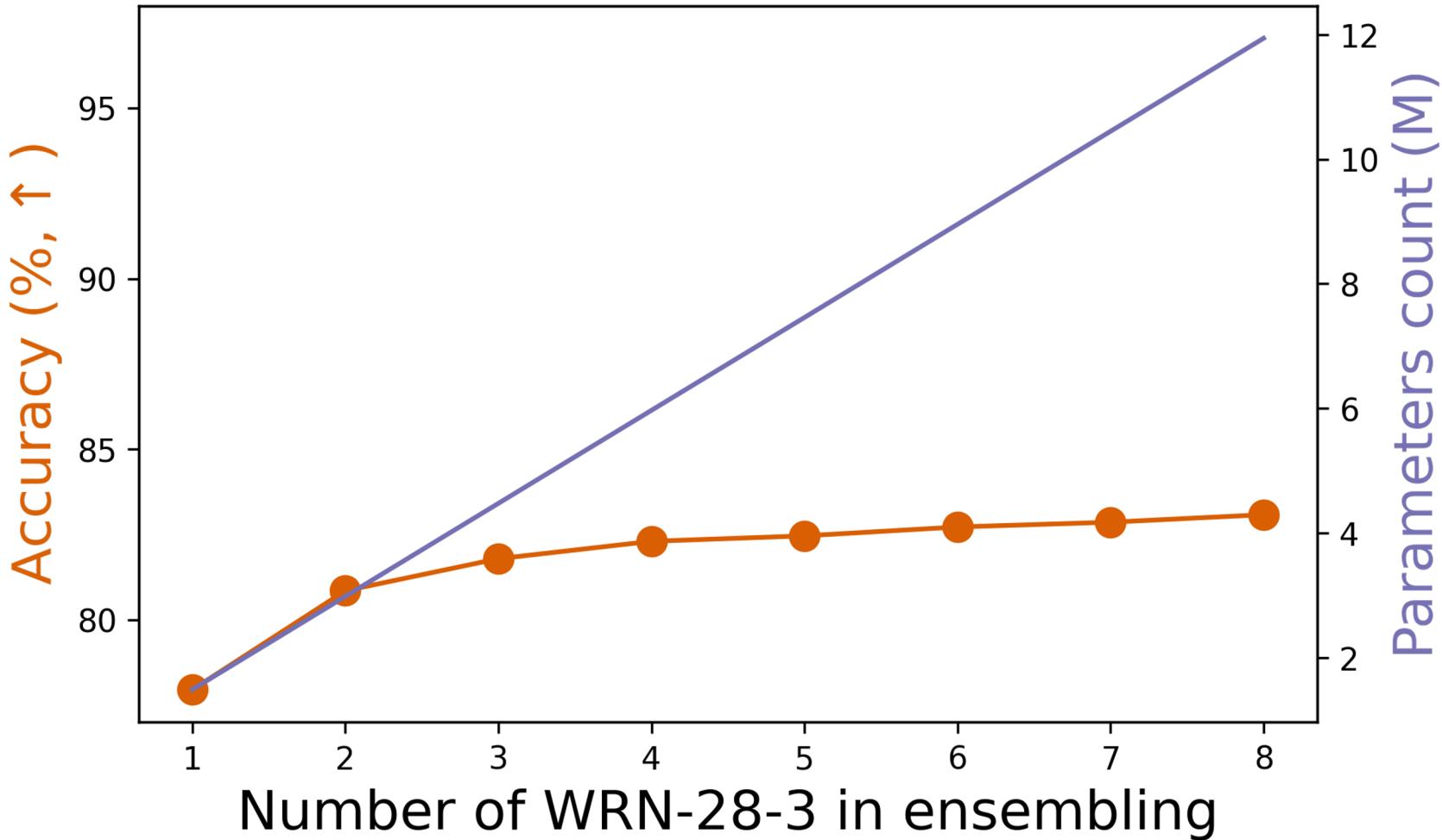


Ensembling improves accuracy ...



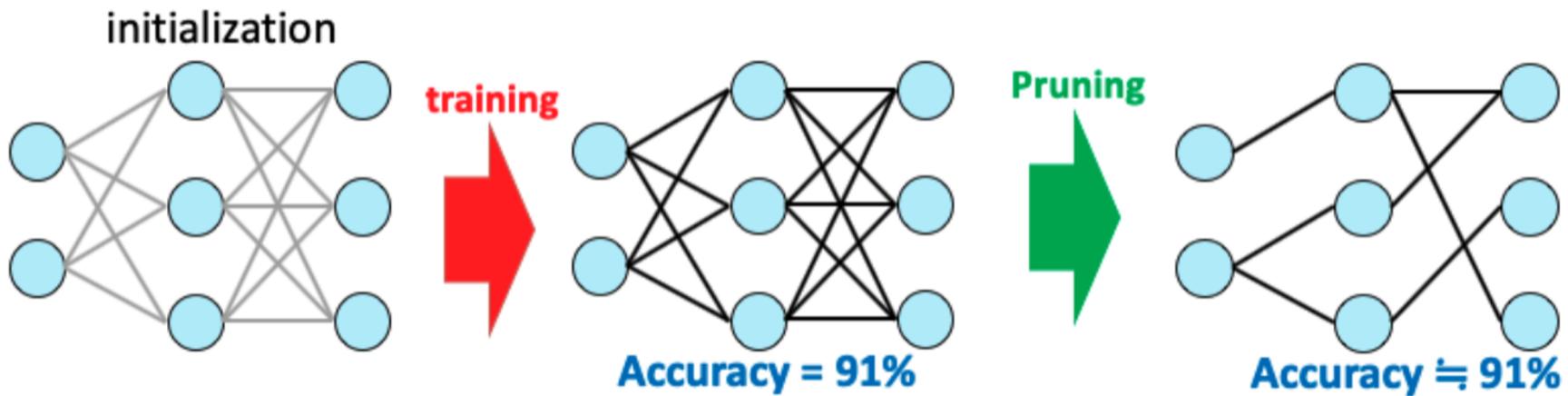


... but ensembling is costly





Idea: leverage network sparsity



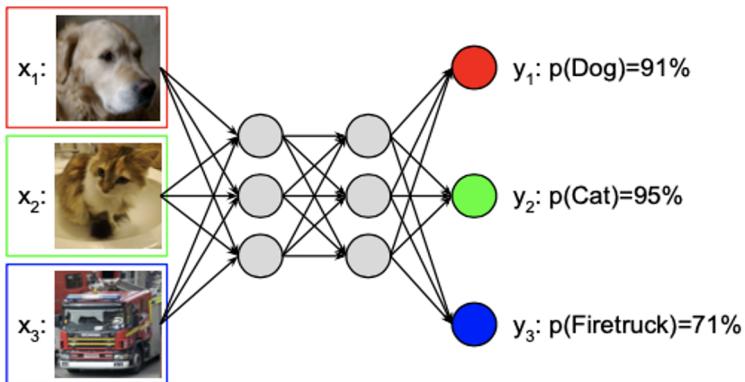
[1] Pruning filters for efficient convnets. Li *et al.*, ICLR 2017

[2] The lottery ticket hypothesis: Finding sparse, trainable neural networks. Jonathan Frankle and Michael Carbin, ICLR 2019

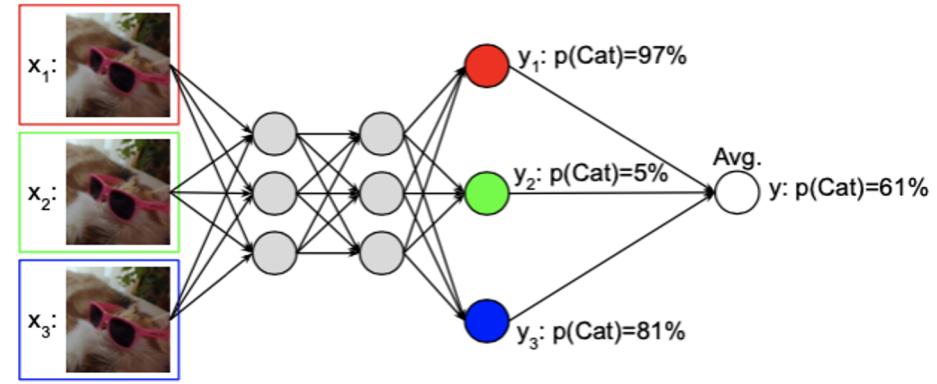
Main idea: multiple subnetworks
inside one base network



Multi-input Multi-output strategy



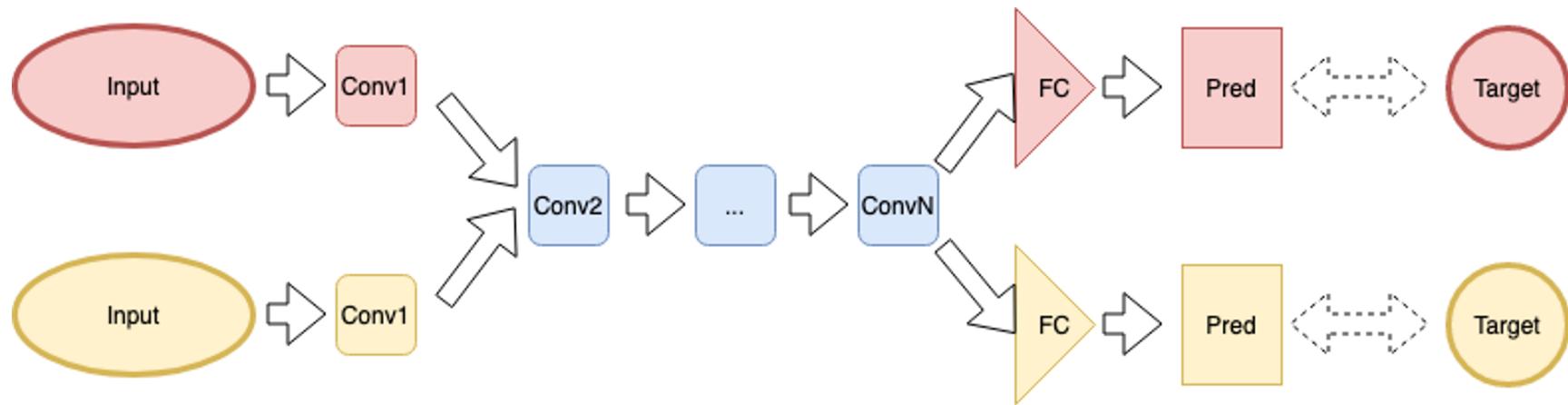
(a) Training



(b) Testing

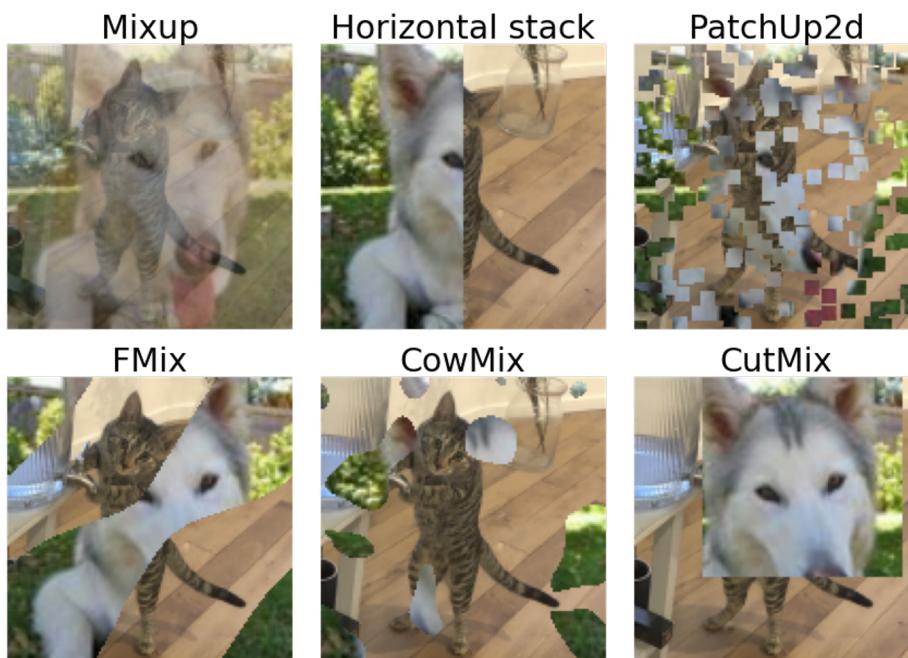
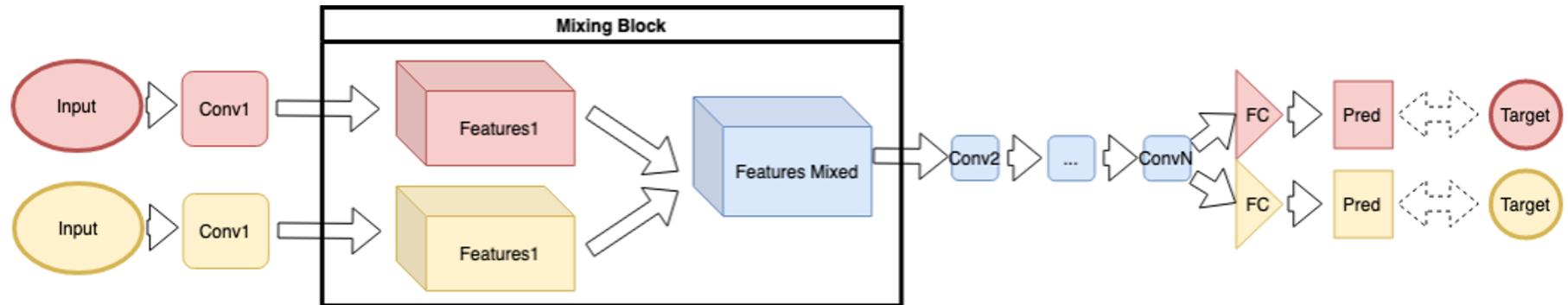


Architecture: all layers shared except the encoders and the classifiers



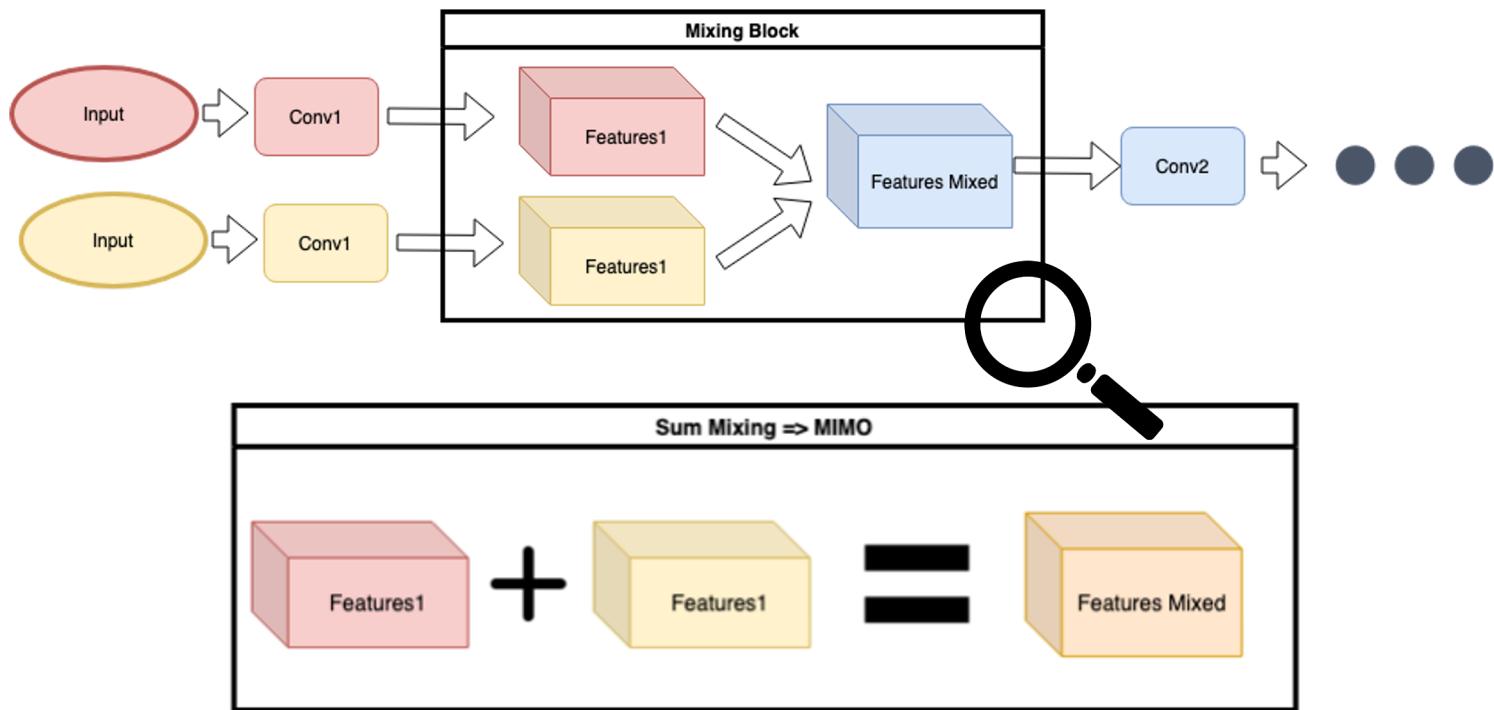


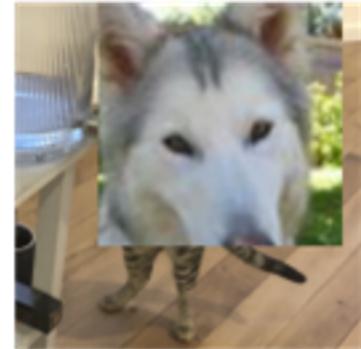
Mixing block combining the inputs' features



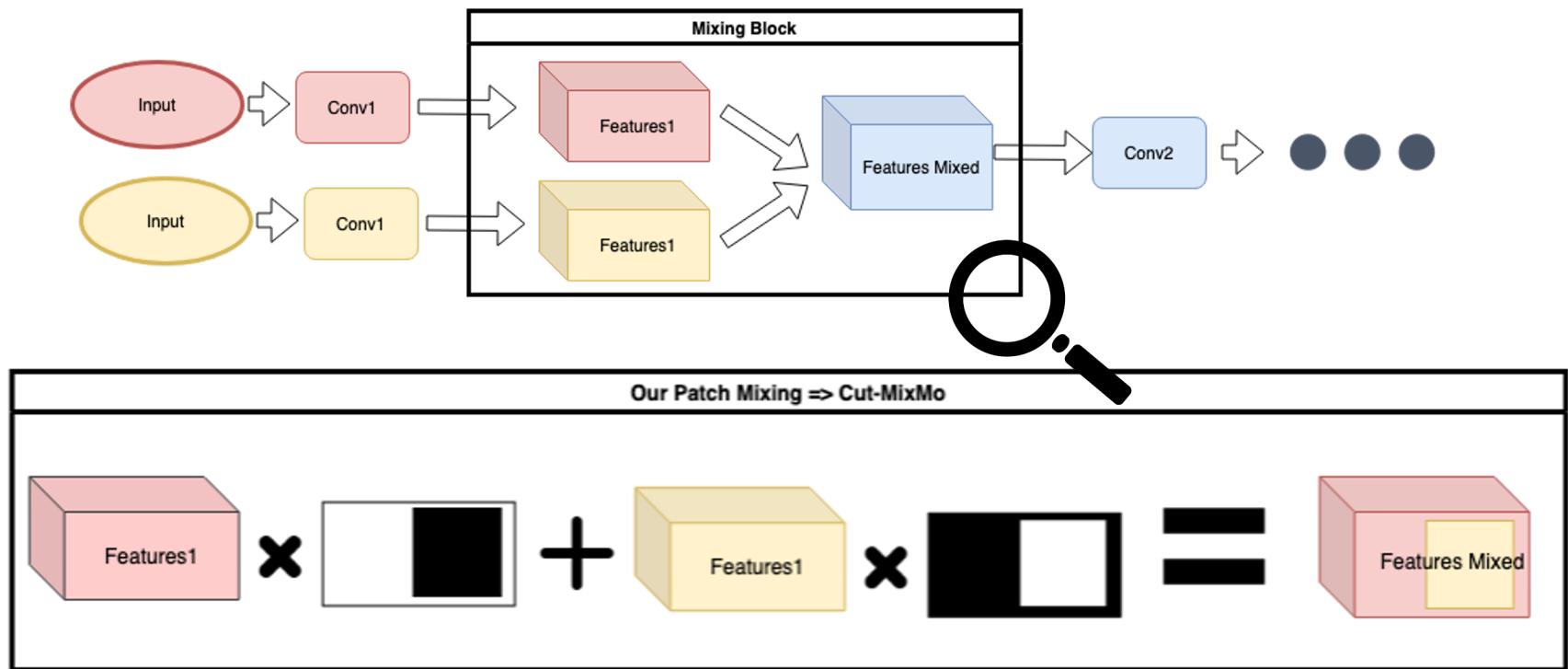


Mixup as mixing block





CutMix as mixing block



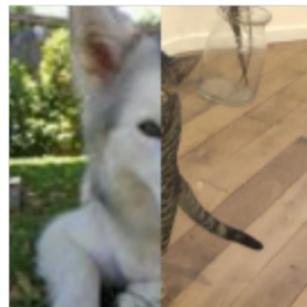


Binary mixing as mixing block improves individual accuracies & ensemble diversity

MixUp
82.5%



Concat.
82.78%



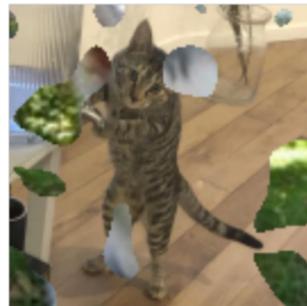
PatchUp
84.16%



FMix
83.76%



CowMix
84.17%



CutMix
84.38%



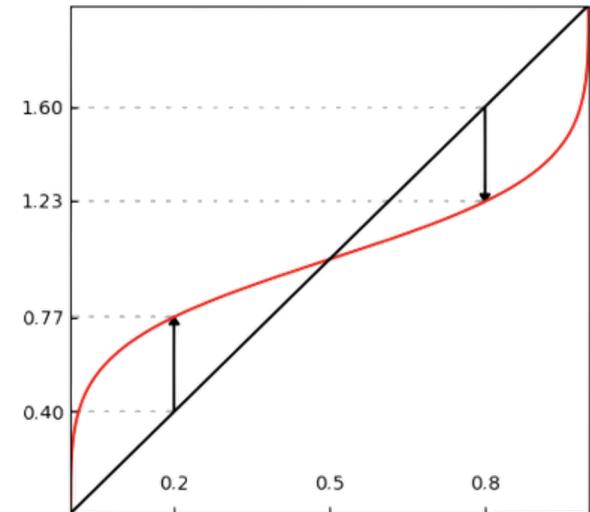
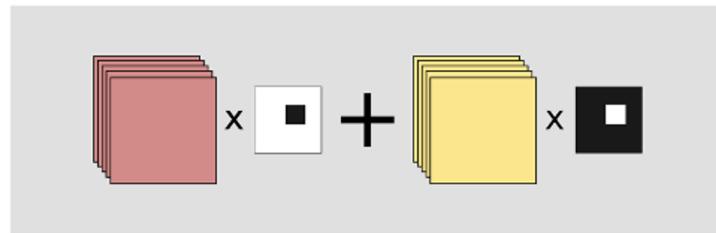


Balancing the training losses

$$\kappa \sim \beta(\alpha, \alpha) \longrightarrow \kappa \rightarrow w_r(\kappa)$$



$$w_r \sim 1_M(\kappa) \rightarrow$$



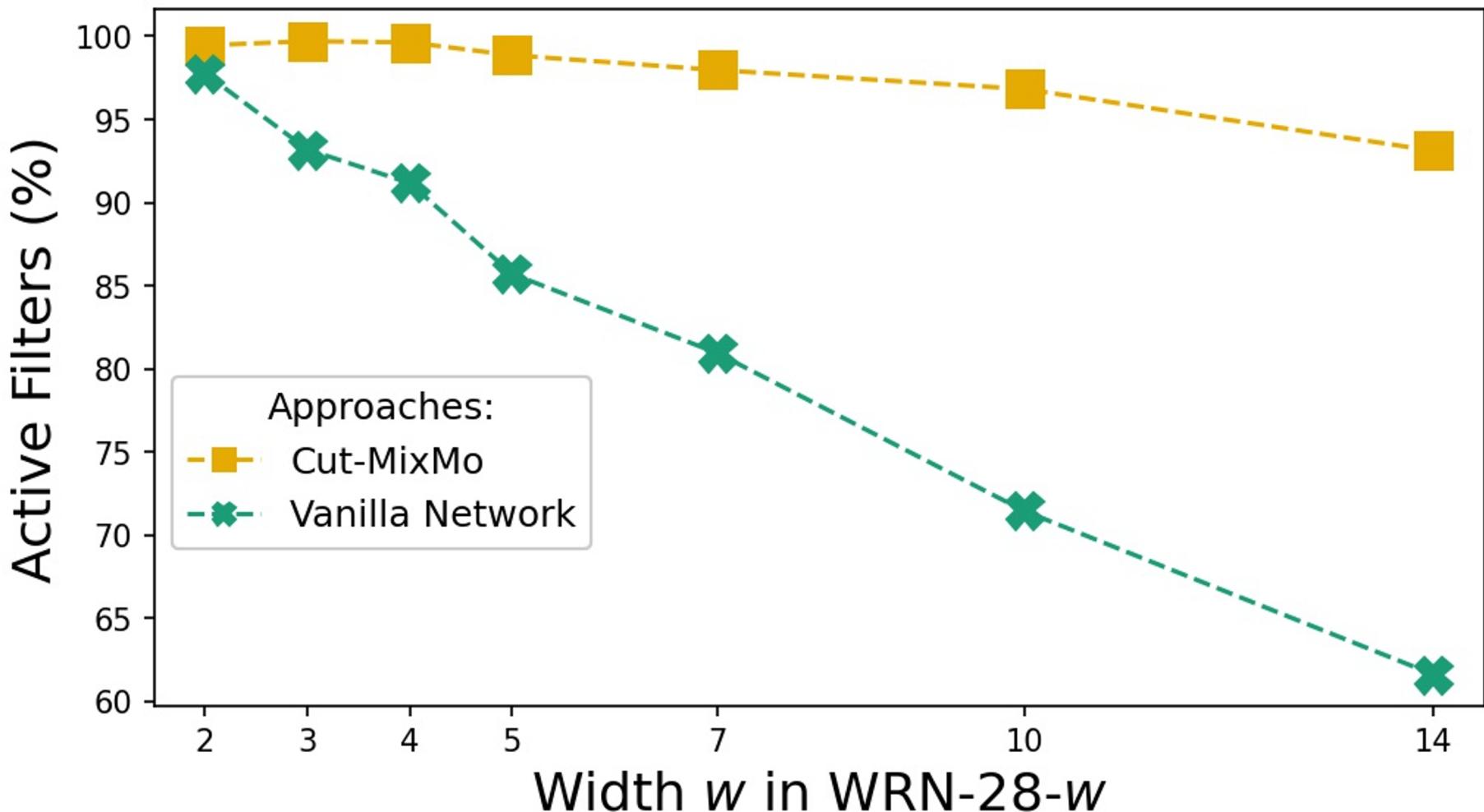
$$\mathcal{L}_{\text{MixMo}} = w_r(\kappa) \mathcal{L}_{\text{CE}}(\overset{\circ}{\text{Cat}}, \text{Cat}) + w_r(1-\kappa) \mathcal{L}_{\text{CE}}(\overset{\circ}{\text{Dog}}, \text{Dog})$$



State of the art on CIFAR and TinyImageNet

Approach	#Params	WRN-28-10		ResNet-18-3	
		CIFAR100	CIFAR10	TinyImageNet	TinyImageNet
Vanilla	1.0	81.63	96.34	65.78	
CutMix	1.0	84.05	97.23	68.95	
Deep Ens.	2.0	83.17	96.67	68.38	
MIMO	1.002	83.06	96.74	68.48	
Cut-MixMo	1.002	85.40	97.51	70.24	

➤ Better leverages over-parameterization





Contributions

❖ Theoretically

Unifying framework for multi-input multi-output ensembling

Connection with data augmentation

❖ Empirically

State of the art at same inference cost as a vanilla network

More in paper: ImageNet, robustness, memory split advantage

<https://github.com/alexrame/mixmo-pytorch>

Merci !