

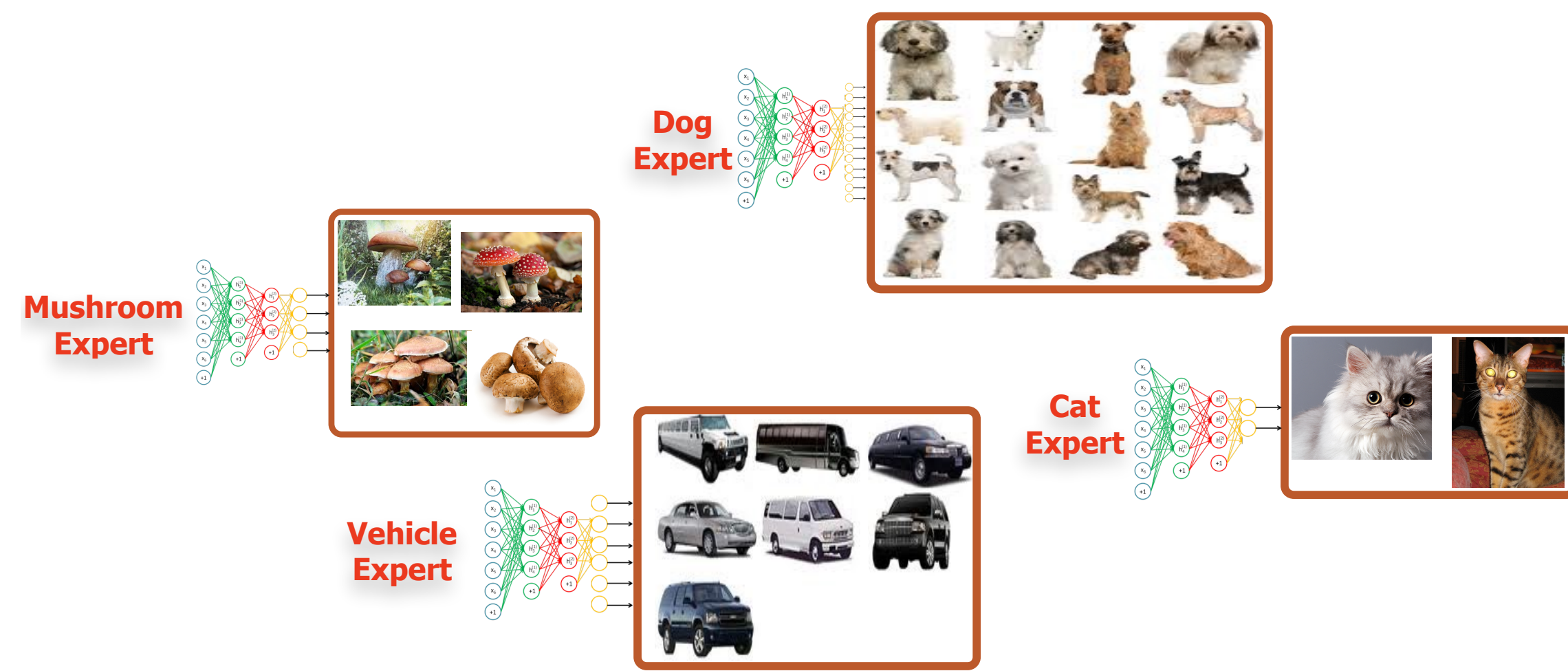
BranchConnect: Image Categorization with Learned Branch Connections

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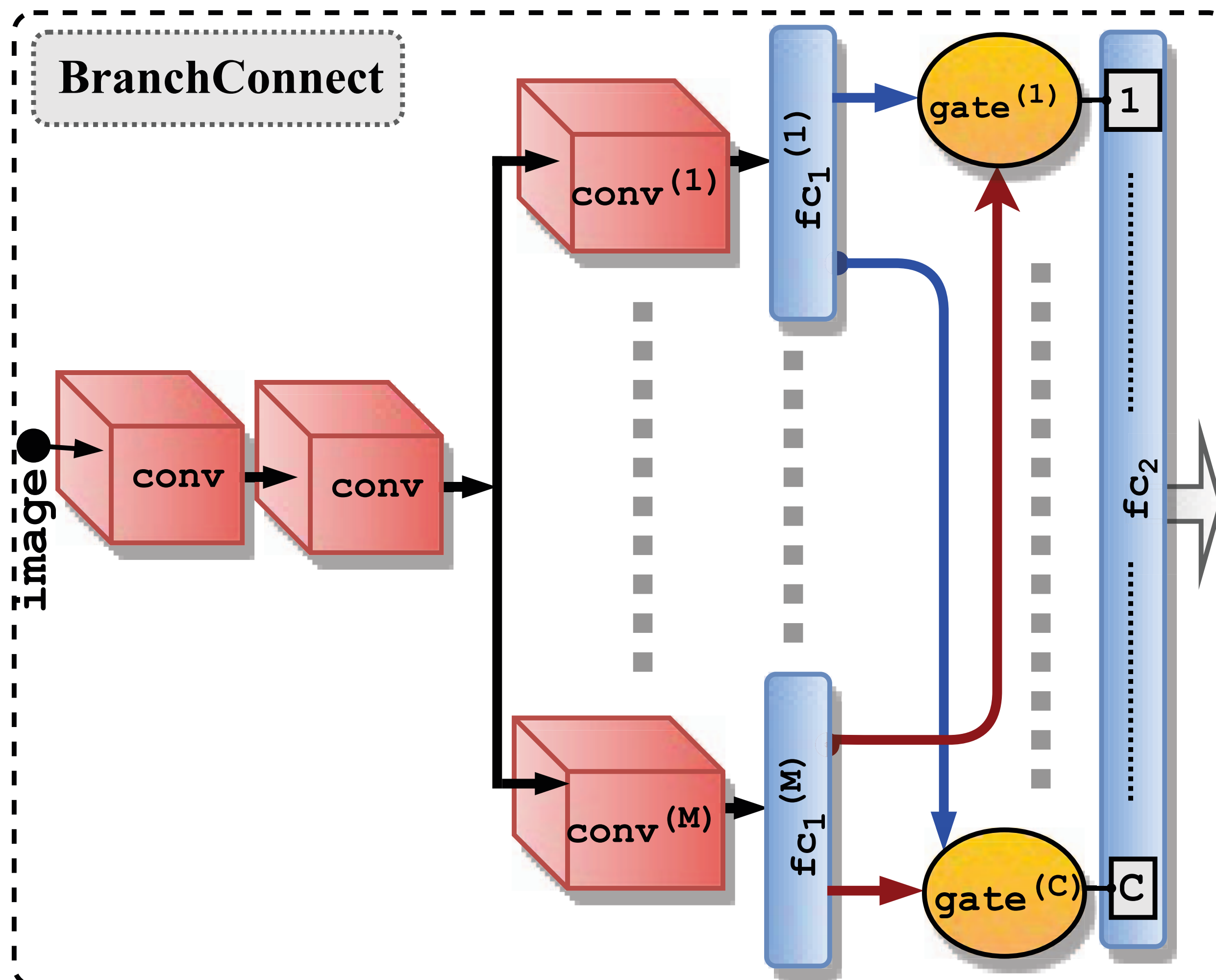
Intuition

The visual system of a layperson is a very good **generalist** that can accurately discriminate coarse categories but lacks the **specialist** eye to differentiate categories that look alike



Contribution

End-to-end learning of separate visual features for the different classes to distinguish.



- The architecture of **BranchConnect** for classification of C classes. The branches implement $M < C$ feature extractors. Class-specific gates connect the M branches to the C classes in the last fully-connected layer.
- The learned gates determines for each class the subset of features to use.

Technical Approach

Goal: learn branch connectivity to classes from data by optimizing training objective

- Minimize $\ell(\theta, \mathbf{g})$ using backpropagation over \mathbf{g} and θ
- During training, we update auxiliary real-valued gates $\mathbf{g}_c^r \in [0, 1]^M$
- Constrain the number of active branch connections per class to be a constant, K (a hyperparameter)

Forward propagation:

1. Stochastically binarize $\mathbf{g}_c^r \in [0, 1]^M$ into $\mathbf{g}_c^b \in \{0, 1\}^M$ s.t.
$$\sum_{m=1}^M g_{c,m}^b = K$$
2. Perform forward pass using binary gates $\mathbf{g}_c^b \in \{0, 1\}^M$

$$F_c = \sum_{m=1}^M g_{c,m}^b \cdot E_m$$

F_c : the c^{th} neuron in the last fully connected layer

E_m : m^{th} branch activations

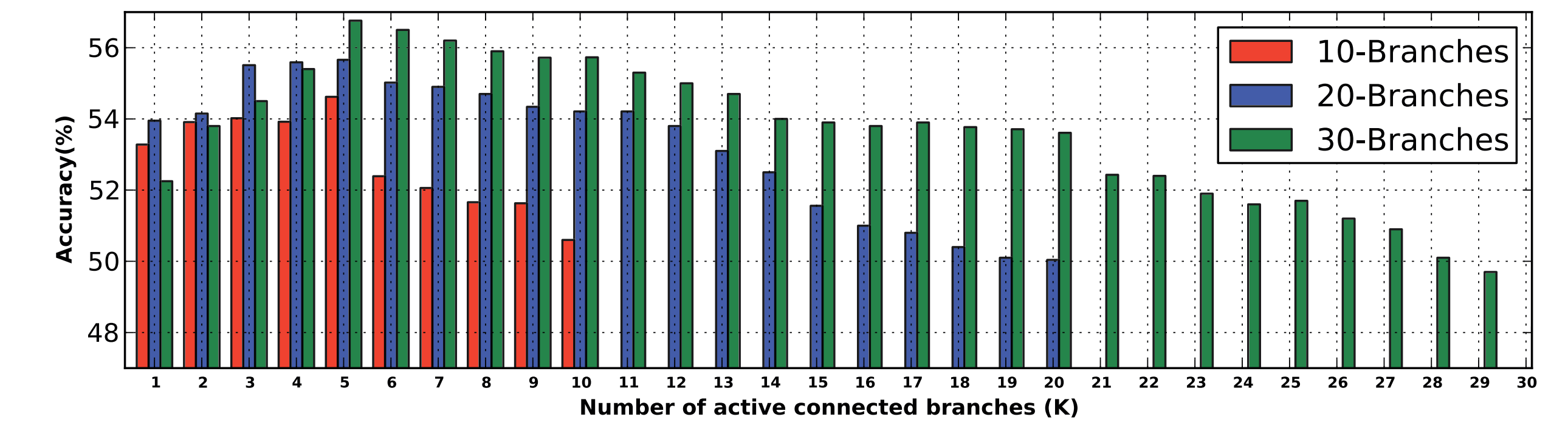
Parameter update:

Compute $\frac{\partial \ell}{\partial g_{c,m}^r}$, and update real-valued masks $\mathbf{g}_{c,m}^r$

$$g_{c,m}^r \leftarrow \text{clip}(g_{c,m}^r - \eta \cdot \frac{\partial \ell}{\partial g_{c,m}^r})$$

Results

CIFAR-100 (100 classes, 50K training examples)



Method	depth	#params	Accuracy
Base Model V1	5	0.15M	44.3
Base Model V2	5	1.20M	40.26
NoFE [1]	6	1.27M	49.09
BRANCHCONNECT G:1/10	5	1.20M	53.28
BRANCHCONNECT G:5/10	5	1.20M	54.62

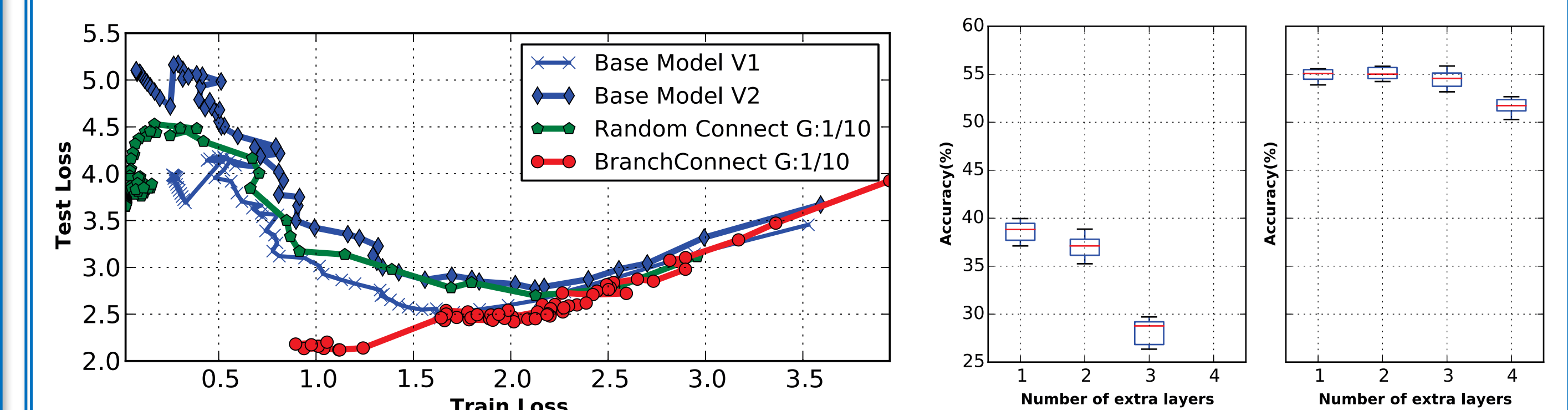
Method	depth	#params	Accuracy
Base Model V1	4	0.18M	54.04
Base Model V2	4	0.64M	50.42
NoFE [1]	5	1.12M	56.24
BRANCHCONNECT G:1/10	4	0.64M	57.34
BRANCHCONNECT G:6/10	4	0.64M	60.27

Method	depth	#params	Accuracy
Base Model V1	9	1.38M	64.73
Base Model V2	9	1.61M	65.24
HD-CNN [2]	n/a	n/a	65.64
NoFE [1]	11	4.66M	65.91
BRANCHCONNECT G:1/10	9	1.61M	66.10
BRANCHCONNECT G:5/10	9	1.61M	66.45

Method	depth	#params	Accuracy
Base Model V1	56	0.86M	69.66
Base Model V2	56	1.47M	70.72
BRANCHCONNECT G:1/10	56	1.47M	71.24
BRANCHCONNECT G:5/10	56	1.47M	71.98

Method	depth	#params	Accuracy
Base Model V1 [1]	56	13.6M	72.23
Base Model V2	56	25.4M	73.12
NoFE [1]	58	25.5M	74.71
BRANCHCONNECT G:1/10	56	25.4M	75.55
BRANCHCONNECT G:5/10	56	25.4M	75.72

BranchConnect acts as regularizer



CIFAR-10 (10 classes, 50K training examples)

Architecture	Method	Accuracy
AlexNet-Quick	Base Model	76.86
	BRANCHCONNECT G:3/5	82.84
AlexNet-Full	Base Model	82.78
	BRANCHCONNECT G:3/5	85.00
ResNet-56 [4]	Base Model	92.04
	BRANCHCONNECT G:3/5	92.46

ImageNet (1000 classes, 1.28M training examples)

Architecture	Method	Accuracy
AlexNet	Base Model	58.71
	NoFE [1]	61.29
	BRANCHCONNECT G:5/10	63.49
ResNet50 [4]	Base Model [7]	76.15
	BRANCHCONNECT G:5/10	77.39
	BRANCHCONNECT G:8/15	77.68
ResNet101 [4]	Base Model [7]	77.37
	BRANCHCONNECT G:5/10	78.19

References

- [1] K. Ahmed et al. "Network of Experts for large scale image categorization.", ECCV 2016.
- [2] Yan et al. "HD-CNN: hierarchical deep convolutional neural networks for large scale visual recognition.", ICCV 2015
- [3] Lin et al. "Network in Network", ICLR 2014.
- [4] He et al. "Deep residual learning for image recognition." CVPR. 2016.