

Team#26 project

"Adaptive Mixture of Low-Rank Factorizations for Compact Neural Modeling" (ICLR 2019)

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Outline

- Key concepts
- Experiment reproduction
- Conclusion
- References

Problem

- Modern NNs have large weight matrices, most are not suitable for mobile deployment
- Low-rank factorization is the popular instrument to reduce matrix size
- Large weight matrix W can be represented as a product of two small rank- d matrices

$$W = UV^{\top} \quad U \in \mathbb{R}^{m \times d}, V \in \mathbb{R}^{n \times d}$$

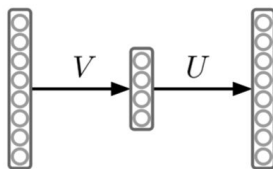
- Large complexity decrease: $O(d(m+n)) \ll O(mn)$
- Problem - loss of information when projecting onto low-dimensional space (Linear bottleneck)

Adaptive mixture of low-rank factorizations

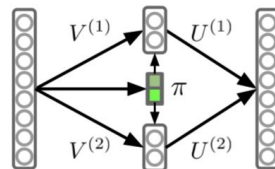
- Make decompositions ~~great again!~~ data-dependent

$$W(h) = \sum_{k=1}^K \pi_k(h) U^{(k)} (V^{(k)})^\top \quad \pi(\cdot) : \mathbb{R}^n \rightarrow \mathbb{R}^K$$

- Replace large matvec with adaptive mixture of low-rank matvecs



(a) regular low-rank



(b) adaptive low-rank

- Strictly speaking, **not a decomposition**, but a new learnable module
- $\pi(\cdot)$ is a small non-linear data-dependent function, e.g. $\pi(h) = \sigma(P(\text{pool}(h)))$, $P \in \mathbf{R}^{K \times n_{\text{pooled}}}$

Experiment reproduction

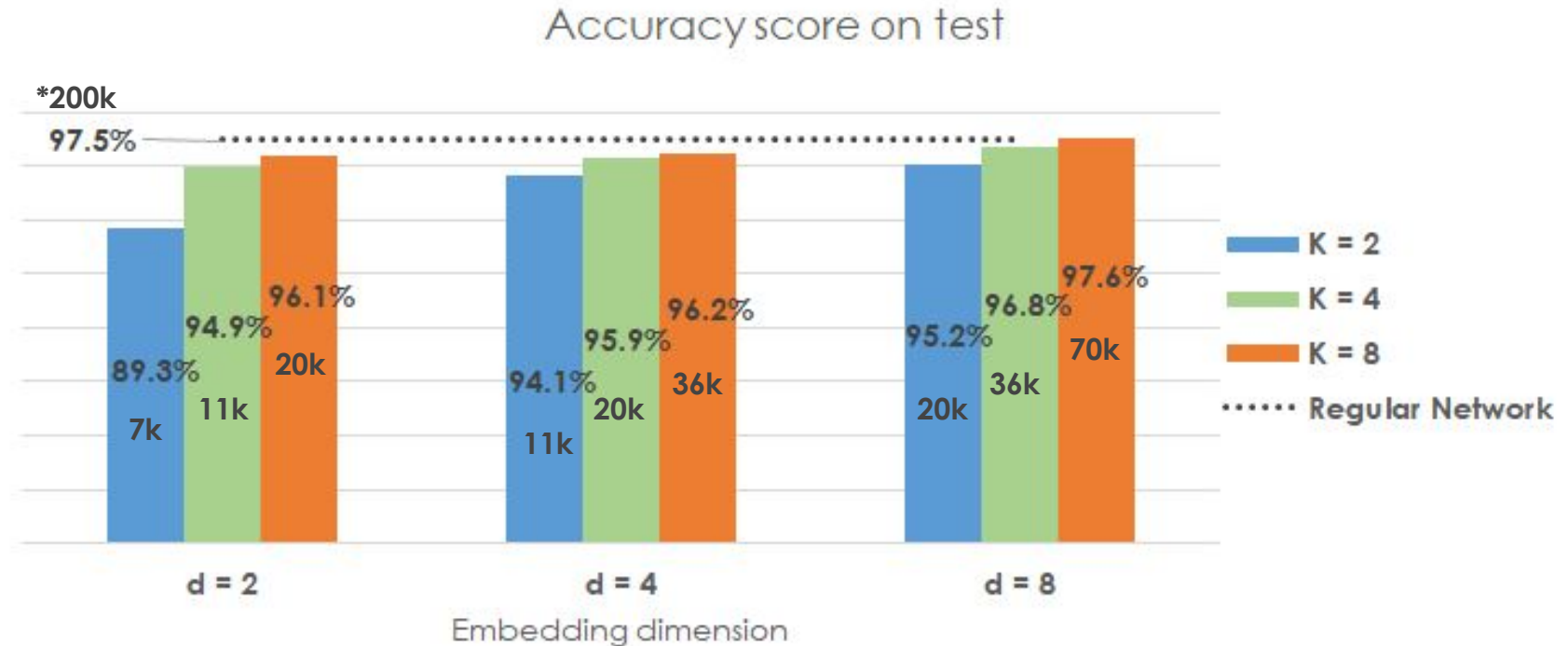
MLP (multi-layer perceptron)

- Digit recognition on MNIST dataset
- Simple one-layer MLP of 300 hidden units, input and output sizes are 784 and 10, respectively
- Rank-d matrices with $d = 2, 4, 8$
- $K = 2, 4, 8$
- Computed mixed weights with x (784×1) reduced to x (28×1)
- Accuracy of adaptive versions of low-rank factorization is 89-97.5%, depending on (K, d)



Experiment reproduction

MLP (multi-layer perceptron): Results

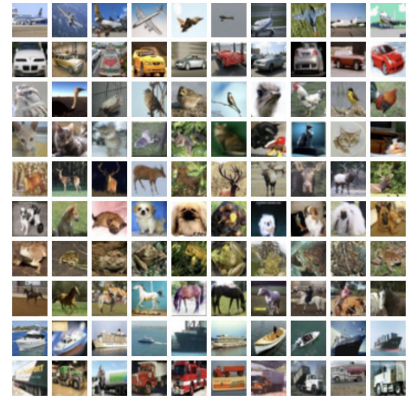


*number of parameters

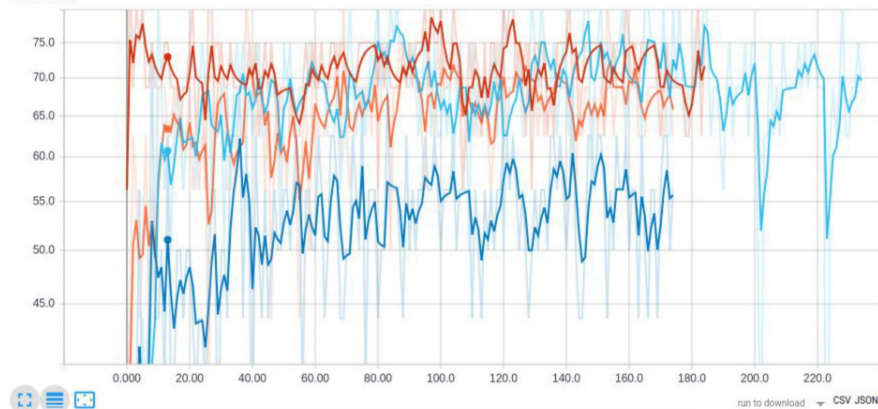
Experiment reproduction

Convolutional Neural Networks

- CIFAR-10
- MobileNet, pointwise convolutions replaced with adaptive low-rank approximation
- Reducing of parametres -> reducing of accuracy
- The best accuracy for MobileNet is 96.875
- The best accuracy for MobileNet-low-rank is 90.625

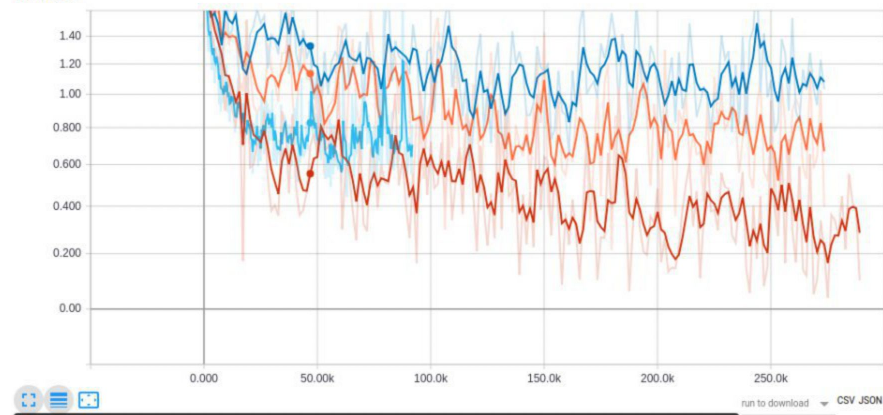


Test/Acc_1



Test/A	Name	Smoothed	Value	Step	Time	Relative
	MobileNet_1545271992	72.96	75.00	13.00	Thu Dec 20, 05:38:21	21m 53s
	MobileNet_LowRank_d=2, K=8, pl_size=8-1545271981	51.03	62.50	13.00	Thu Dec 20, 05:39:27	23m 2s
	MobileNet_LowRank_d=4, K=4, pl_size=8-1545291806	60.72	62.50	13.00	Thu Dec 20, 10:57:13	11m 50s
	MobileNet_LowRank_d=8, K=2, pl_size=8-1545271971	63.36	62.50	13.00	Thu Dec 20, 05:39:19	23m 22s

Train/Loss



Name	Smoothed	Value	Step	Time	Relative
MobileNet_1545271992	0.5542	0.6986	46.89k	Thu Dec 20, 06:04:54	48m 30s
MobileNet_LowRank_d=2, K=8, pl_size=8-1545271981	1.327	1.328	46.89k	Thu Dec 20, 06:07:22	51m 11s
MobileNet_LowRank_d=4, K=4, pl_size=8-1545291806	0.8276	0.8154	46.92k	Thu Dec 20, 12:33:00	1h 47m 41s
MobileNet_LowRank_d=8, K=2, pl_size=8-1545271971	1.135	1.096	46.89k	Thu Dec 20, 06:07:11	51m 31s

	best acc Top-1	Params
MobileNet-CIFAR10	96.875	121.61k
MobileNet-CIFAR10 low-rank, (2,8)	81.25	23.1k
MobileNet-CIFAR10 low-rank, (8,2)	90.625	46.52k
MobileNet-CIFAR10 low-rank, (4,4)	81.25	46.7k

Conclusion

- adaptive low-rank factorization is an original method proved to have results much better than regular low-rank decomposition
- it achieves up to 60-80% compression (dependent on the model) without significant decrease of accuracy
- in contrast to regular low-rank methods it learns non-linear low-rank manifolds due to learnable

$$\pi(\cdot)$$

References

- [1] T. Chen, J. Lin, T. Lin, C. Wang, D. Zhou, S. Han, Adaptive Mixture of Low-Rank Factorizations for Compact, 2018
- [2] François Chollet. Xception: Deep learning with depth-wise separable convolutions. *arXiv preprint*, 2016.

Code

<https://github.com/zuenko/ALRF>