

Exploiting Elasticity in Tensor Ranks for Compressing Neural Networks

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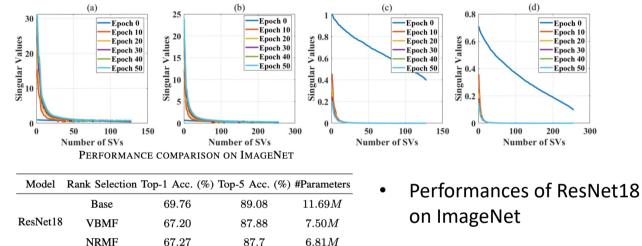
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Motivation:

Elasticities in depth, width, kernel size and resolution have been explored in compressing deep neural networks (DNNs). Recognizing that the kernels in a convolutional neural network (CNN) are 4way tensors, we further exploit a new elasticity dimension along the input-output channels, dynamically and globally searching for the reduced tensor ranks during training.

Experiments:

• Effect of regularizer on singular values of the parameters



Our Method:

Rank Selection we introduce a nuclear-norm-based regularizer, and demonstrate $\arg \min_{R_m^{(1)}} \frac{-\tau_m}{\sum_{i_m=1}^{S_m} \lambda_m^{(i_m)}}$ how it can dynamically locate the ranks during training. $L_n = \frac{1}{2M} \sum_{n=1}^{M} \left(tr(\boldsymbol{W}_m^{(1)} \boldsymbol{W}_m^{(1)T}) + tr(\boldsymbol{W}_m^{(2)} \boldsymbol{W}_m^{(2)T}) \right)$ $W_m^{(1)} W_m^{(1)T} S_m =$ $U_{m}^{(1)}$ $V_{m}^{(1)T}$ S_m **Matricization** S_m S_m S_m $\sum_{j_m=1}^{\kappa_m} \xi_m^{(j_m)}$ \mathcal{W}_m $\xi_m^{(j_m)}$ $\arg \min_{R_m^{(2)}} \frac{\mathcal{L}_{J_m=1}^{J_m=1,m}}{\sum_{j_m=1}^{T_m} \xi_m^{(j_m)}} \ge p$ Mode-4 Mode-3 matricization matricization NRMF rank selection strategy $W_m^{(2)} W_m^{(2)T} T_m =$ $U_{m}^{(2)}$ $V_m^{(2)T}$ T_m T_m T_m $(W_m^{(2)})$ $\underline{T_m \times D_m} \times D_m$ $S_m \times D_m \times D_m$ S_m I_m T_m T_m T_m T_m

Reference:

S. Nakajima, M. Sugiyama, S. D. Babacan, and R. Tomioka, "Global analytic solution of fully-observed variational bayesian matrix factor- ization," *Journal of Machine Learning Research*, vol. 14, no. Jan, pp. 1–37, 2013.