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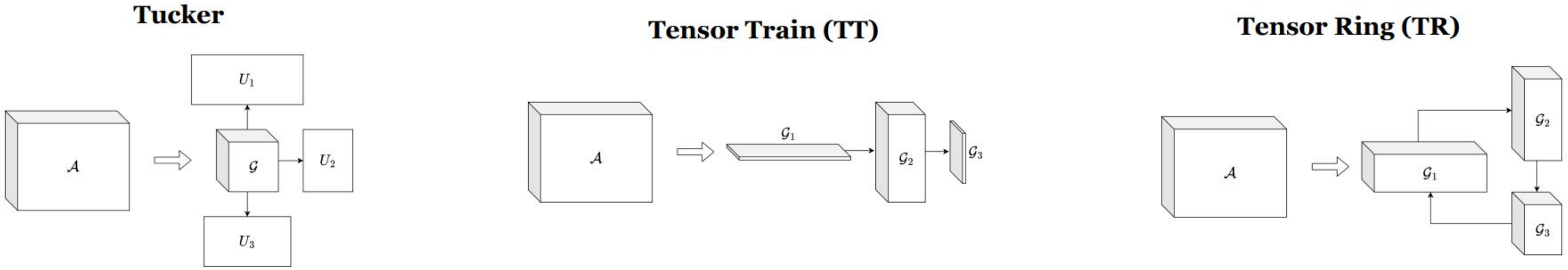
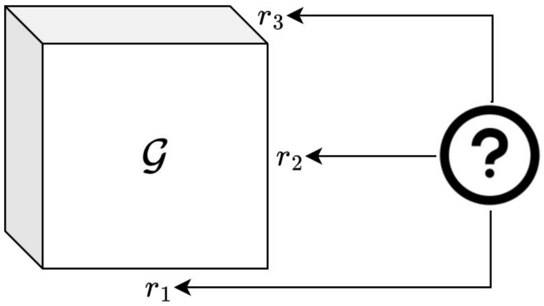
MARS: Masked Automatic Ranks Selection in Tensor Decomposition

Paper Review

UFO Team

Motivation&Problem: Tensor decomposition methods are effective in compression and acceleration of neural networks. However, to achieve balance between compression and performance we need to carefully select tensor ranks.





- Typical hyperparameter selection techniques, like cross-validation, are poorly suited for the choice of multiple tensor ranks.
- Existing approaches for core ranks selection are not general. They also could require significant computational overhead.

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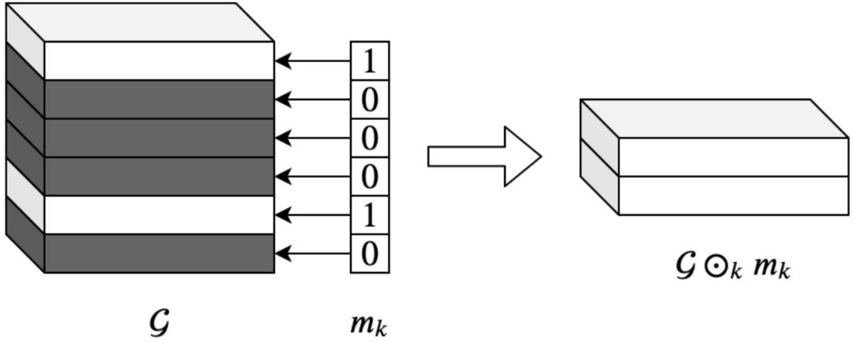
Proposed method

- Ranks can be represented by binary masks over tensor dimensions



- Bayesian model for these binary masks is proposed, MAP estimate is considered

$$p\left(Y, \boldsymbol{m}, \boldsymbol{G} \mid X\right)=\prod_{i=1}^{N} p\left(y_i \mid x_i, \boldsymbol{G} \odot \boldsymbol{m}\right) p(\boldsymbol{m}) p(\boldsymbol{G})$$

- Learned masks are binarized and applied to core tensors, resulting in compressed model

$$\mathcal{G}_k \odot \boldsymbol{m} := \mathcal{G}_k \odot_{k_1} m_{k_1} \cdots \odot_{k_p} m_{k_p}$$

Model

$$p\left(Y, \boldsymbol{m}, \boldsymbol{G} \mid X\right) = \prod_{i=1}^{N} p\left(y_i \mid x_i, \boldsymbol{G} \odot \boldsymbol{m}\right) p\left(\boldsymbol{m}\right) p\left(\boldsymbol{G}\right)$$

Prior over masks is assumed to be Bernoulli with the success parameter π

$$p\left(\boldsymbol{m}\right) = p\left(\boldsymbol{m} \mid \pi\right) = \prod_{k} \prod_{s=1}^{r_k} \pi^{m_k(s)} (1-\pi)^{1-m_k(s)}$$

MAP estimate is considered. This discrete optimization problem can be reduced to continuous optimization

$$\sum_{i=1}^{N} \log p\left(y_i \mid x_i, \boldsymbol{G} \odot \boldsymbol{m}\right) + \log p\left(\boldsymbol{m}\right) + \\ + \log p\left(\boldsymbol{G}\right) \longrightarrow \max_{\boldsymbol{m}, \boldsymbol{G}}$$

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Model

Under the assumption that q(m) is a factorized Bernoulli distribution, problem from previous slide is equivalent to

$$\mathbb{E}_{\boldsymbol{m}\sim q_{\boldsymbol{\phi}}(\boldsymbol{m})}\left[\sum_{i=1}^{N}\log p\left(y_i \mid x_i, \boldsymbol{G}\odot\boldsymbol{m}\right)\right]+$$
$$+\sum_{k}\sum_{s=1}^{r_k}\left[\phi_k(s)\log\pi+(1-\phi_k(s))\log(1-\pi)\right]+$$
$$+\log p\left(\boldsymbol{G}\right)\longrightarrow\max_{\boldsymbol{\phi},\boldsymbol{G}}.$$

After applying reparameterization trick, we can use stochastic gradient descent to get MAP estimate of G (cores) and ϕ (probability parameter from Bernoulli distribution of masks).

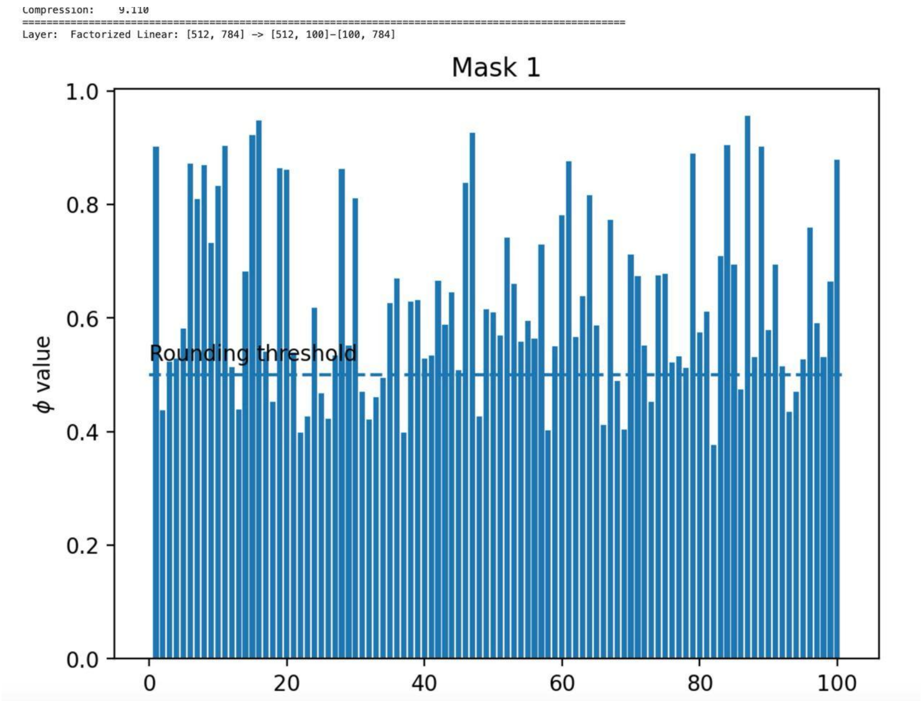
Finally, binary masks are obtained by rounding ϕ

Mode-k Hadamard product between cores and corresponding masks gives compressed tensors.

Reproducing paper results

https://github.com/xiyori/mars-reproducibility

- The code provided by the authors only reproduces 1 experiment with a simple fully-connected model
- We implement 2 more experiments: LeNet-5 on MNIST and ResNet-110 on CIFAR10
- Our results align with the paper sufficiently well



Reproducing paper results: LeNet-5

- Tucker decomposition for convolution
- Low-rank factorization for linear (Skeleton decomposition!)

$$A = UV^T,\ U \in \mathbb{R}^{m\times r}, V \in \mathbb{R}^{n\times r}$$

Model	Compression	Accuracy	Speed-up (inference)	Slow-down (training)
		Original results		
Baseline	$1\times$	99.2%	$1\times$	-
MARS + Tucker	$10 \pm 0.8\times$	$99.0 \pm 0.07\%$	$1.19 \pm 0.01\times$	-
5-ensemble	$2\times$	99.5%	faster in parallel	-
		Our reproduction		
Baseline	$1\times$	99.3%	$1\times$	$1\times$
MARS + Tucker	$7.1\times$	$99.0 \pm 0.08\%$	$1.32 \pm 0.04\times$	$1.04\times$
5-ensemble	$1.4\times$	99.1%	faster in parallel	$5.2\times$

Reproducing paper results: ResNet-110

- Tensor Train for convolutions in 2nd and 3rd blocks
- Naive: 2d + 1 tensors r_{k-1} x n_k x r_k
- Proper: similar number of tensors r_{k-1} x n_k x m_k x r_k, inspired by Garipov et al. (2016)

Model	Compression	Accuracy	Slow-down (inference)	Slow-down (training)
Original results				
Baseline	1×	92.6%	-	-
MARS (naive)	7.0×	90.7%	-	-
MARS (proper)	5.5×	91.1%	-	-
Our reproduction				
Baseline	1×	92.3%	1×	1×
MARS (naive)	at least 2.7×	at least 89%	1.60×	2.9×
MARS (proper)	at least 2.3×	?%	1.54×	2.8×

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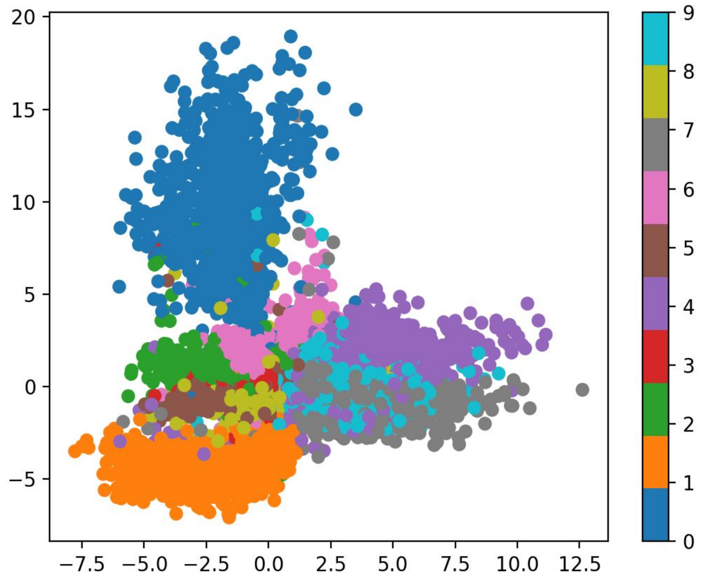
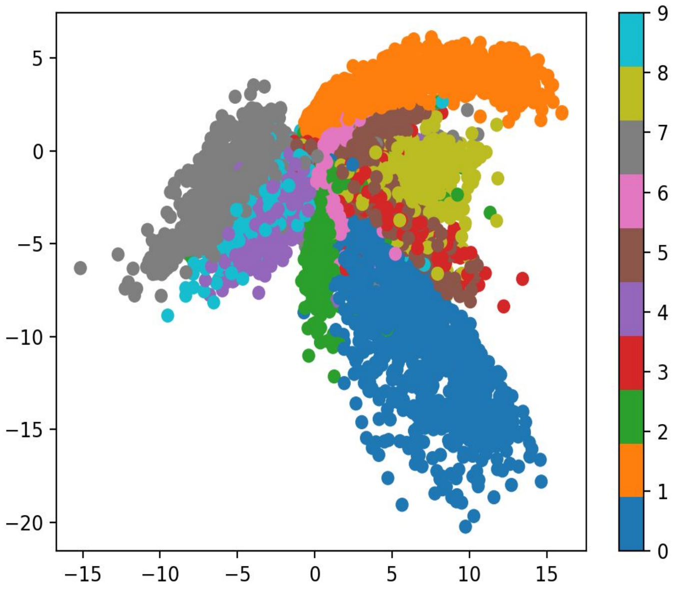
MARS for AutoEncoders



Factorized autoencoders latent space
Compression: 3.819



Base autoencoders latent space's latent space

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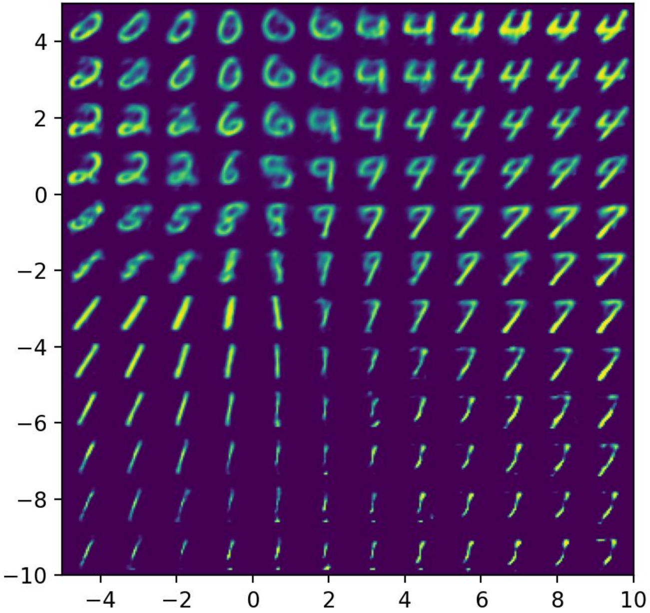
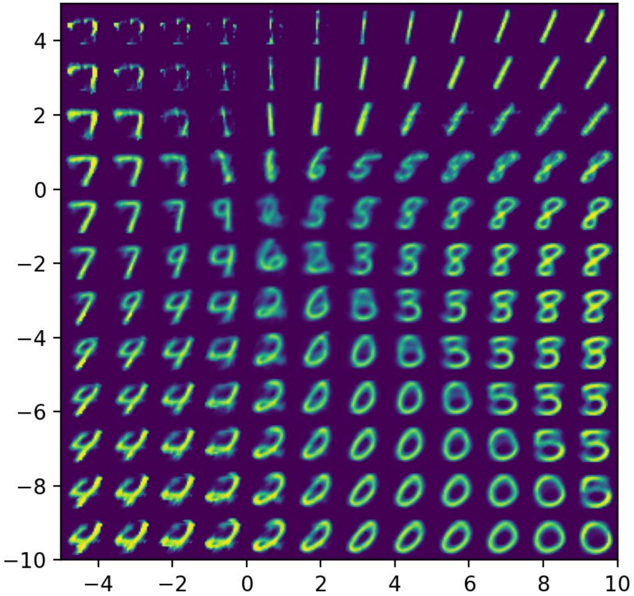
MARS for AutoEncoders

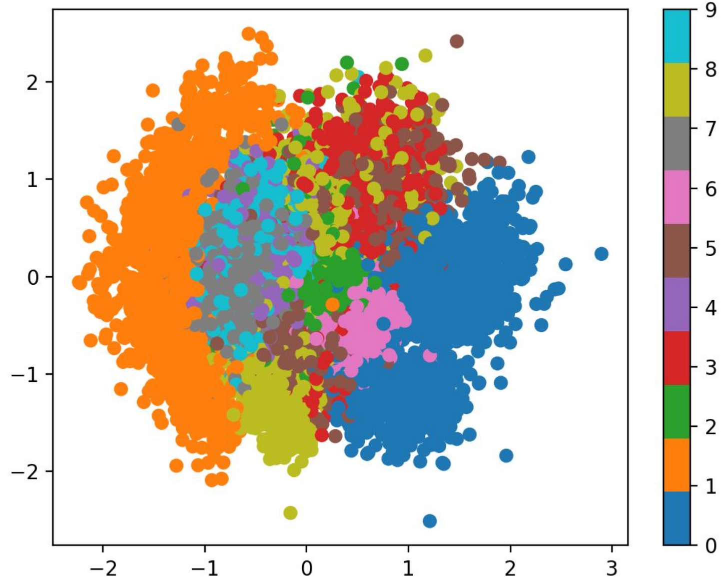


Factorized autoencoder reconstruction
Inference speedup: 1.11

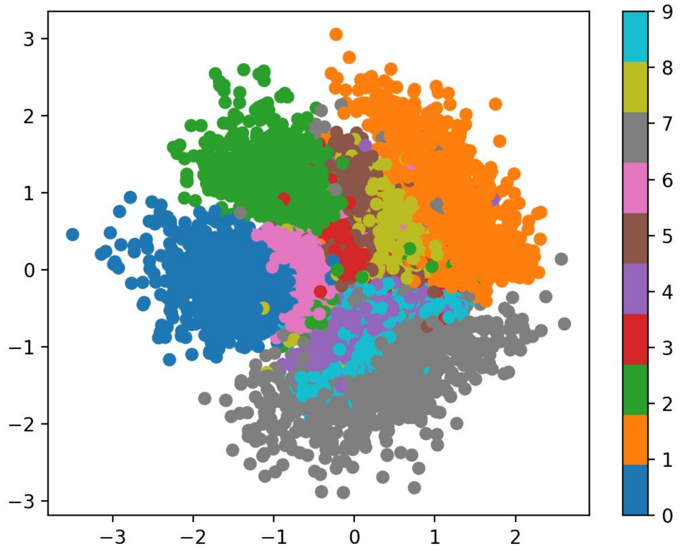


Base autoencoder reconstruction

MARS for VAE



Factorized VAE latent space
Compression: 5.383



Base VAE latent space

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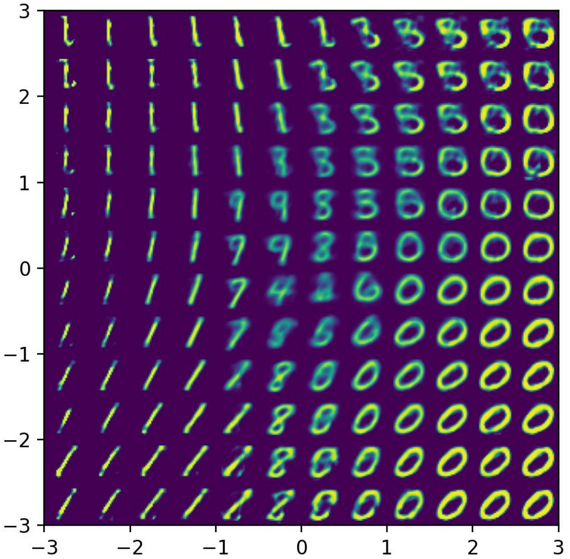
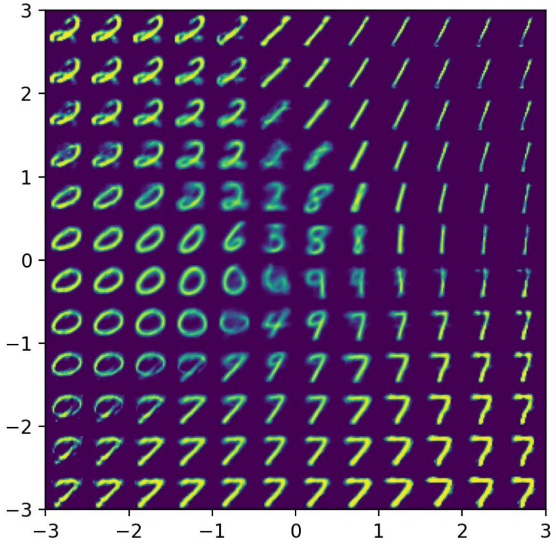
MARS for VAE



Factorized VAE reconstruction
Inference speedup: 1.12



Base VAE reconstruction

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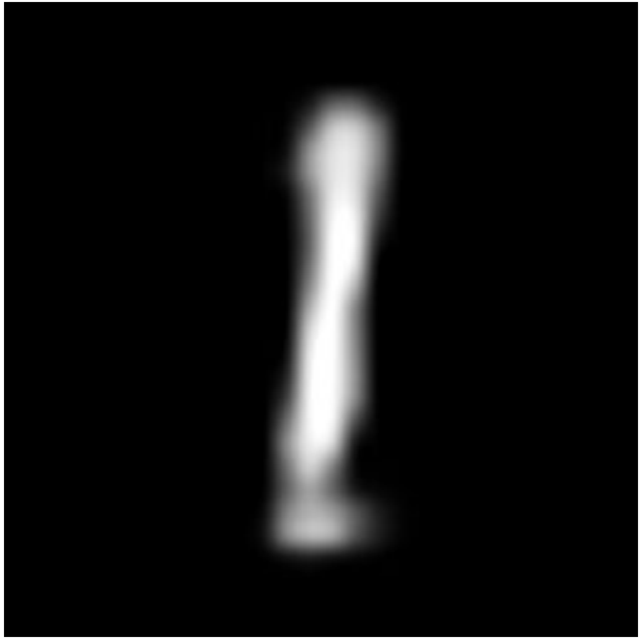
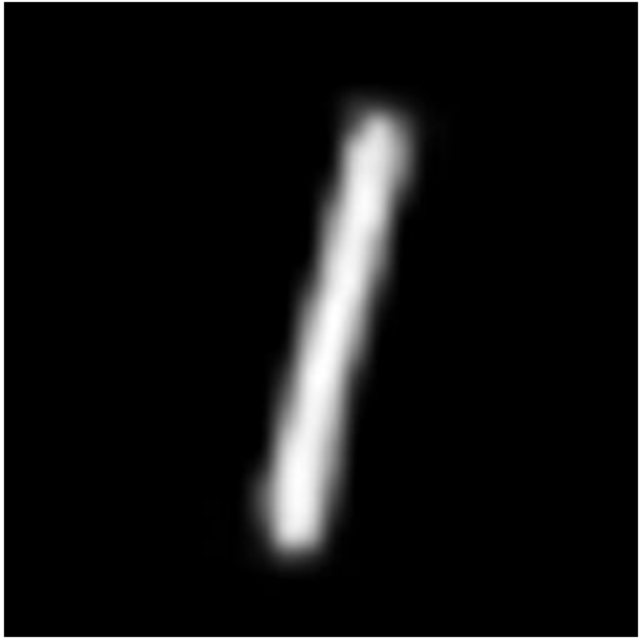
MARS for VAE



Factorized VAE transition



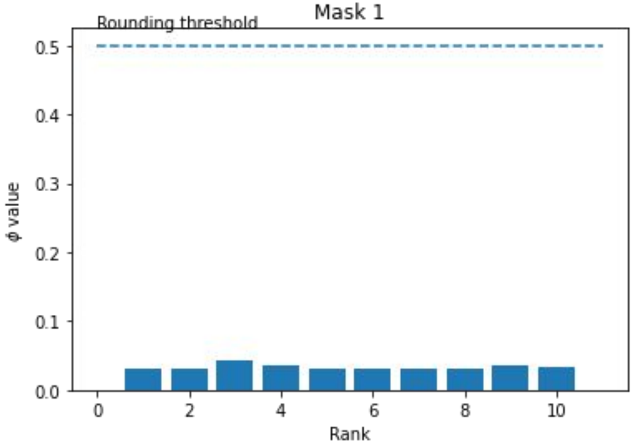
Base VAE transition

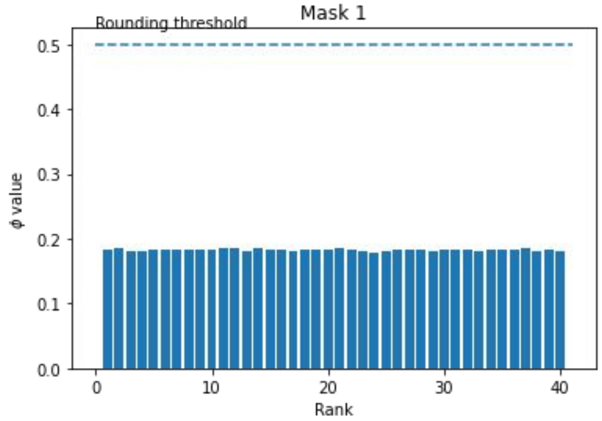
MARS for U-Net

Approach for U-Net:
- Replace ordinary convolution blocks with either ones based on TT or Tucker decomposition (similar to famous approach with MobileNet convolutions)

As a result, size of model decreases from the start

Challenges:
- Hard to make large model to “take off”
- During training MARS more likely to not find any structure inside of models at all and give a zero mask
- Training process take 2x-3x more time, than for ordinary U-Net, because requires some time after convergence to find a mask





Conclusion

Model Advantages

- **Universal** - applicable to various tensorized models
- **Sensible** - closely rank approximation
- **Effective** - much better than manual selection of ranks and no worse than specialized rank selection schemes
- **Efficient** - no extra computational cost
- **Scalable** - easy tensorization of ResNet-110
- **Consistent** - learned masks probabilities are close to hard values {0, 1}

Model Disadvantages

- In practice it is difficult to choose hyperparameters
- Ensemble learning approach is quite long
- Model is working long for TensorTrain rank selection

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Experimental applications

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