# Improving accuracy of neural networks compressed using fixed structures via doping

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## Summary


- Efficient structures (circular, block-circular, Kronecker products (KP) etc) have shown remarkable results in compressing NNs
  - *KP can compress LSTMs in IoT workloads by 15-38x*, outperforming traditional compression techniques
- However, hard to scale these techniques for larger networks
- We introduce doping - A sparse matrix overlay that provides additional degrees of freedom to matrix expressed using efficient structures
  - To use doping, we need to overcome co-matrix adaption using co-matrix row regularization

***" Using Doped KP, we can compress a large language model with LSTM layers of size 25 MB by 25x with 1.4% loss in perplexity score outperforming other traditional compression techniques (pruning, LMF etc) by a large margin"***


## Introduction of Kronecker Products

- Let $A \in R^{mxn}$, $B \in R^{m1xn1}$ *and* $C \in R^{m2xn2}$ then, the KP between B and C is given by

$$A = B \otimes C$$

$$A = \begin{pmatrix} b_{1,1} \circ C & \cdots & b_{1,n1} \circ C \\ \vdots & \ddots & \vdots \\ b_{m1,1} \circ C & \cdots & b_{m1,n1} \circ C \end{pmatrix}$$

- B and C are referred to as Kronecker factors (KF) of A and m = m1xm2 and n = n1xn2
- *If m = 154, n =164, m1 = 11, n1=41, m2 = 14, n2 = 4, we get 50x compression!*
- We can use more than 2 KFs. Eg -

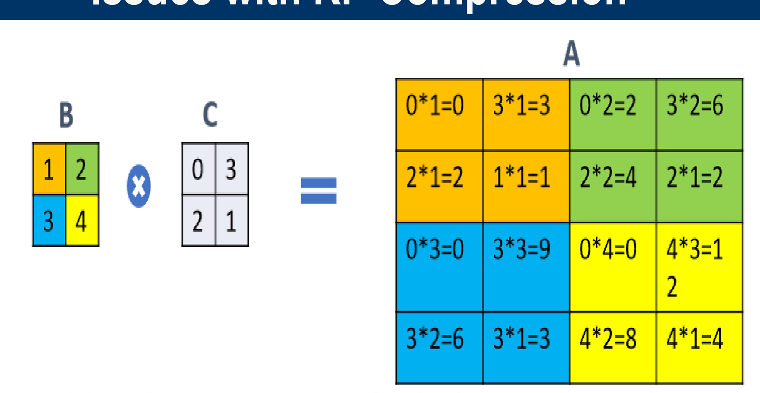
$$W = W1 \otimes W2 \otimes \ldots Wn.$$

- Prior work [1] showed –
  - How many number of KF matrices, n, should we choose
  - The impact on inference run-time when RNN are expressed as KP of 2 matrices
  - We can compress IoT Workloads by 15-38x
- However, this work does not scale to large networks

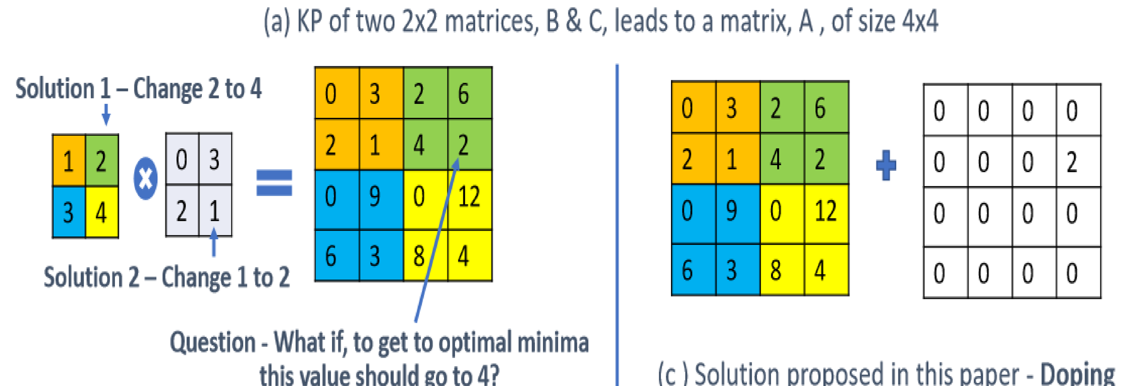
## Applying KP to a large Language Model

- Applied KP to medium Language Model from [2].
  - LSTM layers with matrices of size 2600x1300 and layers total size of 25 MB.
  - Baseline Perplexity of 82.07
- Result of KP Compression –
  - *Compression by a factor of 338x*
  - *Perplexity of 104.03, perplexity loss of 38%!*
- [1] suggests using Hybrid KP to recover lost accuracy
  - HKP can recover the lost accuracy, but compression reduces to a factor of 5x
- ***Questions***
  ***" Why does KP Compression lead to loss in accuracy for large models?"***
  ***" How can you scale KP to larger networks without sacrificing accuracy or giving up on their significant compression benefits"***

## Issues with KP Compression




(a) KP of two 2x2 matrices, B & C, leads to a matrix, A , of size 4x4




(b) Changing a single element in B/C changes 4 elements in A. This restricts the expressibility of A. Solution 1 doubles the values of all elements in the green boxes in A. Thus, we do not reach the optimal solution. Similar observation can be made for Solution 2

(c ) Solution proposed in this paper - **Doping**
Add a sparse matrix (94% sparsity) to A to provide additional degrees of freedom to the elements in matrix A. This allows the matrix to be updated such that it reaches the optimal minima

## Doped Kronecker Products (DKP)

$$W = M_{kp} + M_{sp}, where\ M_{kp} = B \otimes C \ - (1)$$

- Sparsity of $M_{sp}$ determines the amount of compression
- For example, if W is of size 100x100, B and C are of size 10x10, then 95% sparsity in $M_{sp}$ will lead to 14x compression and 90% sparsity in $M_{sp}$ will lead to 8.4x compression
- During the initial phase of training, $M_{sp}$ is dense. As training progresses, $M_{sp}$ reaches the required sparsity level

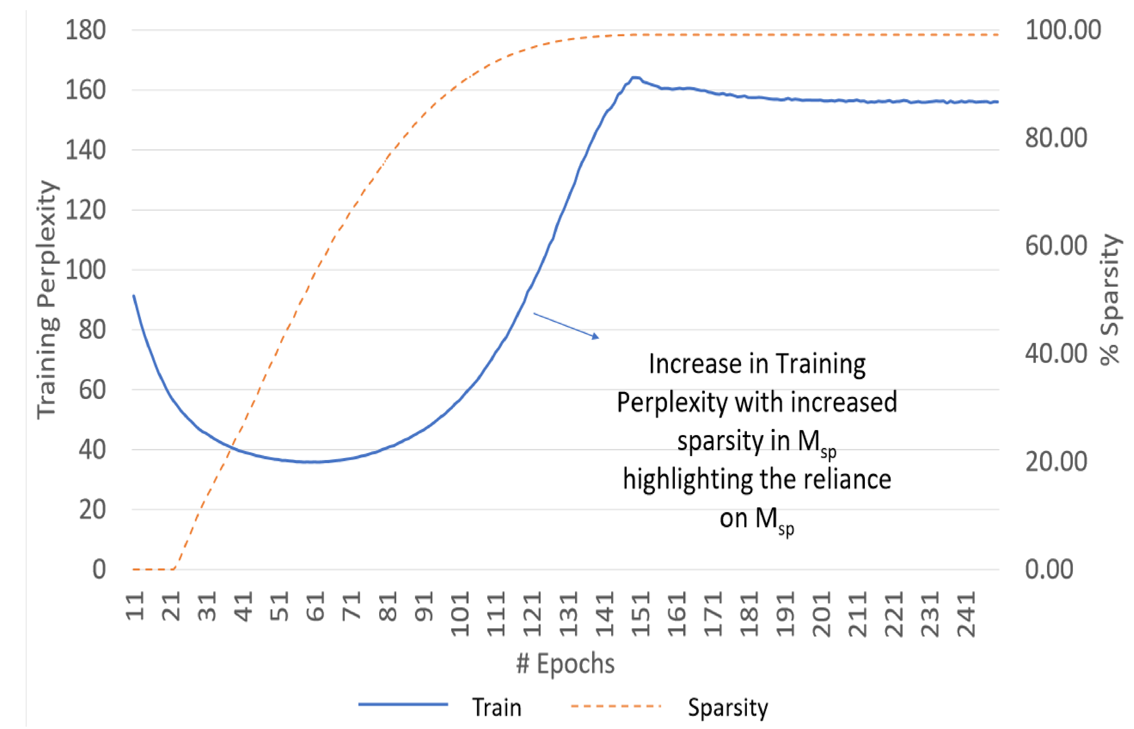
## Co-matrix Adaptation

- Applying DKP as in equation 1 does not work. Table 1 shows the result of applying DKP as in equation 1.

*Table 1*

| | | |
|---|---|---|
| Baseline Perplexity | 82.04 | |
| Compression Factor | 338x | 100x |
| Sparsity of $M_{sp}$ | 100% | 99.93% |
| DKP Perplexity | 104 | 138.3 |

- DKP as shown in equation 1 does not work because of co-matrix adaptation, as shown below:




- Possible methods to overcome CMA:

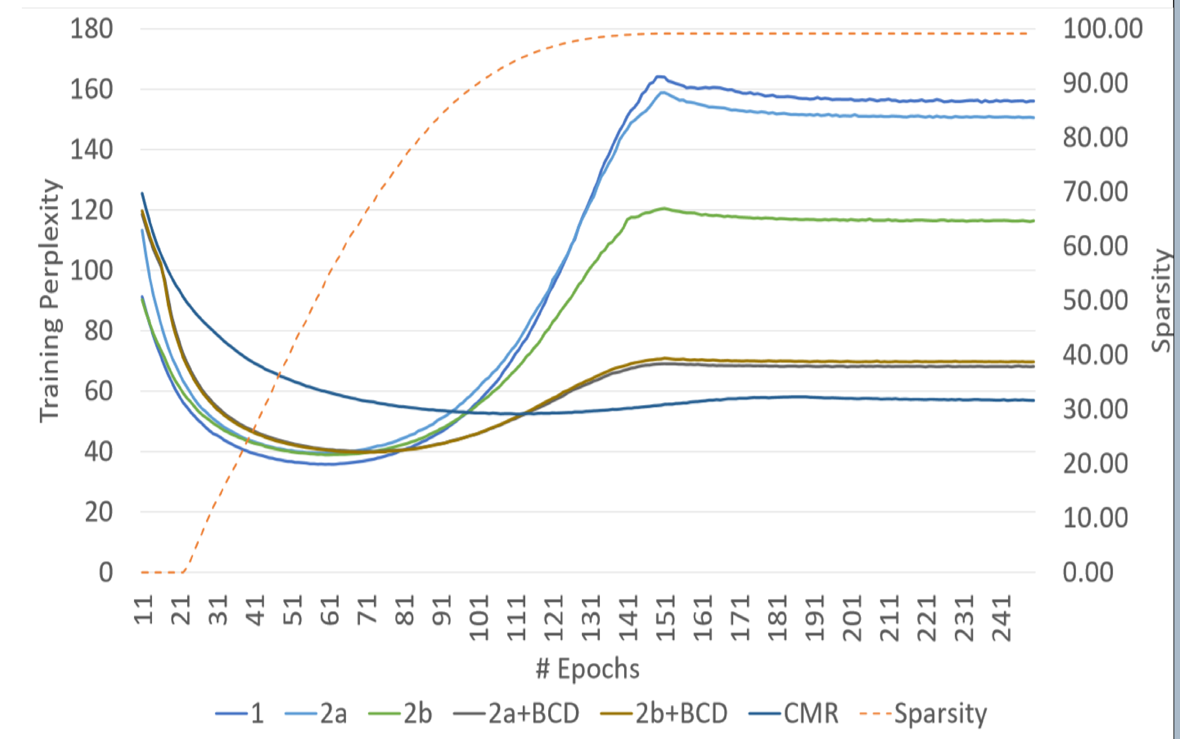
$$W = B \otimes C + \beta * M_{sp}, \min||\beta|| \ - (2a)$$
$$W = \alpha * (B \otimes C) + \beta * Msp, \min||\beta|| \ - (2b)$$

- Equation 2a and 2b can be further trained using Block Circular Descent (BCD)

## Co-matrix Row Dropout Regularization (CMR)

- Equations 2a and 2b, help manage CMA to a certain extent. We asked ourselves, could we do better?
- Our hypothesis: During CMA, incoming neurons from the $M_{kp}$ matrix and the $M_{sp}$ matrix learn to co-adapt, leading to lost capacity
- Introduce stochastic behavior where either the Mkp neuron or the Msp neuron are not available to drive the output neuron
- CMR:

$$W = (B \otimes C) \odot b_1 + Msp \odot b_2$$
$$where\ b_1 \sim Bernoulli(p), b_2 \sim Bernoulli(p)$$




## Results

| | Compression Factor | Test Perplexity |
|---|---|---|
| Baseline | 1 | 82.04 |
| 4-bit quantization [3] | 8 | 83.84 |
| 3-bit quantization [4] | 10.67 | 83.14 |
| Tensor Train Decomposition [5] | 1.67 | 168.64 |
| Weight Distortion with Pruning [6] | 10 | 84.64 |
| Low-rank matrix factorization | 20 | 114.29 |
| HMD [7] | 20 | 105.43 |
| HKD [1] | 20 | 99.882 |
| Magnitude Pruning | 20 | 85.14 |
| **This work (DKP+CMR)** | **25** | **83.24** |

## Read our papers for more details

*Full paper available on arxiv, scan this QR code for link*

*This work*

*Prior work on KP Compression*

## References


[1] Compressing RNNs for IoT devices by 15-38x using Kronecker Products
[2] Recurrent Neural Network Regularization
[3] Weighted-Entropy-based Quantization for Deep Neural Networks
[4] Retraining-Based Iterative Weight Quantization for Deep Neural Networks
[5] Compression of Recurrent Neural Networks for Efficient Language Modeling
[6] DeepTwist: Learning Model Compression via Occasional Weight Distortion
[7] Run-Time Efficient RNN Compression for Inference on Edge Devices