Neural Networks Weights Quantization: Target None-retraining Ternary (TNT)

Tianyu Zhang*, Lei Zhu†, Qian Zhao‡, and Kilho Shin§

*WeBank, †Harbing engineering university, ‡University of Hyogo and §Gakusyuin University

Introduction Target Non-retraining Ternary (TNT)

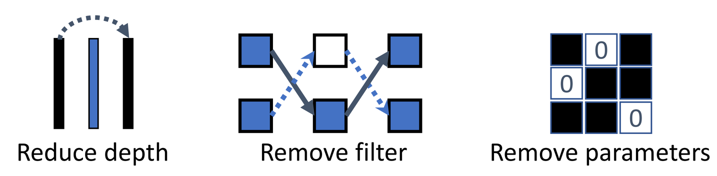
Motivation

Deep neural networks (DNNs) are widely used in many resource constrained edge devices, such as mobiles, robots, cars, and satellites, however, such devices have:

- **less** memory
- **low** powerful CPUs
- **limited** batteries

Flexibility of neural network compression

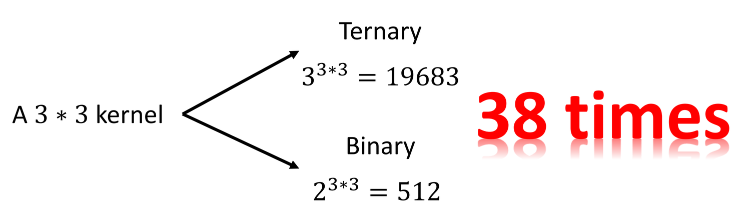
- Some parameters have limited effect
- Expression redundancy
- Reduce the performance of the model



Ternary Quantization

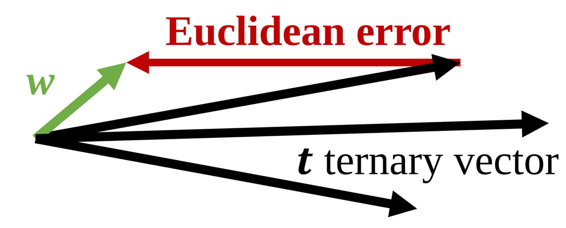
Parameters quantization of DNNs is one technique that represents DNNs' weights only using 1 or 2 bits. Rather than binary quantization, the ternary quantization approach attracts more attention by:

- Better representing ability than binary
- Reducing memory requirements
- Simplifying multiplication operations



Euclidean error method

Finding a scalar λ and a $\boldsymbol{t}$, where the members of $w^*$are -1, 0, or 1, to minimize **the Euclidean error**.



$$\min \|\boldsymbol{w} - \lambda \boldsymbol{t}\|_2$$

Problems of Euclidean error

The Euclidean error are widely used in many approaches, however, they have some practical problems:

- Searching range is too large, which is 3^N and N is the dimension of the vectors
- Converting needs training and fine-tuning, which is TIME CONSUMING
- Result CANNOT be controlled

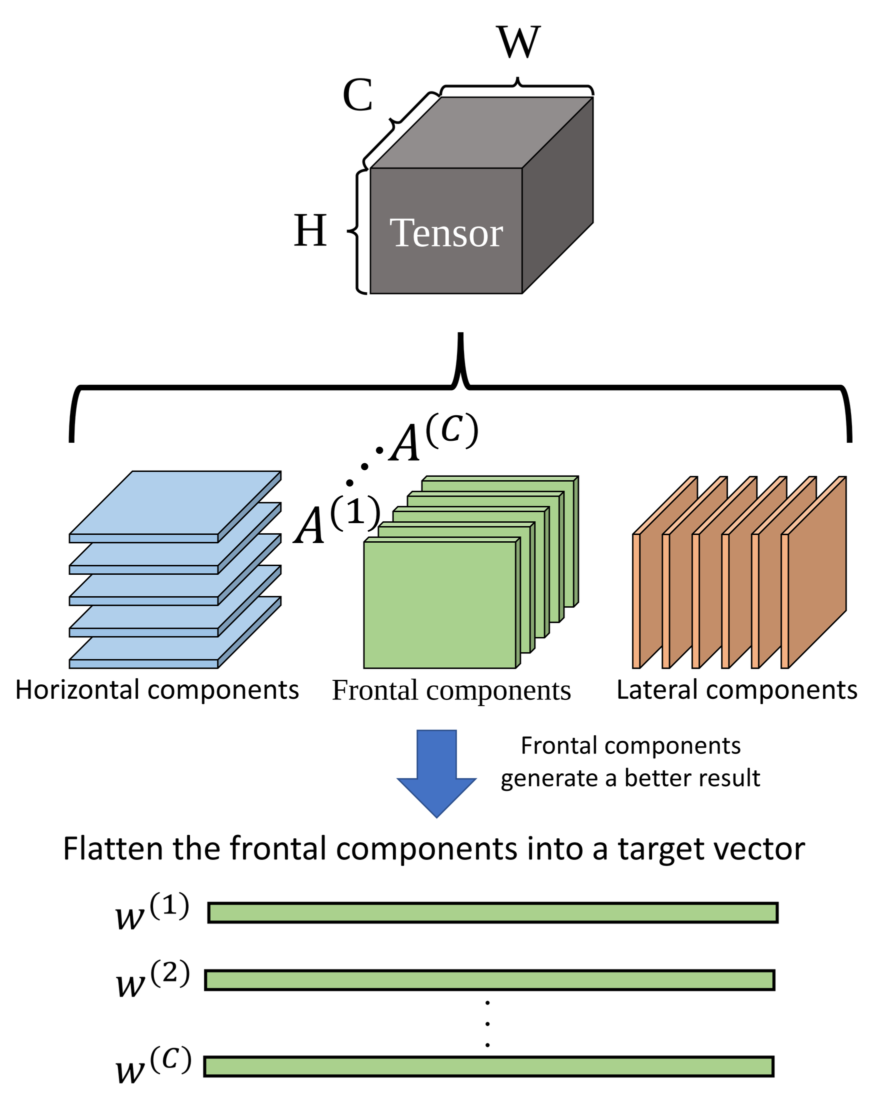
Target Non-retraining Ternary (TNT) cosine similarity based

- Reducing searching range to **N**, e.g., reducing **2187** times searching range of a 3*3 kernel.
- Non-retrain and Non-fine-tuning and converting time only costs **O(Nlog N)**
- Result is controllable

Methodology

Tensor Decomposition and Vectorization

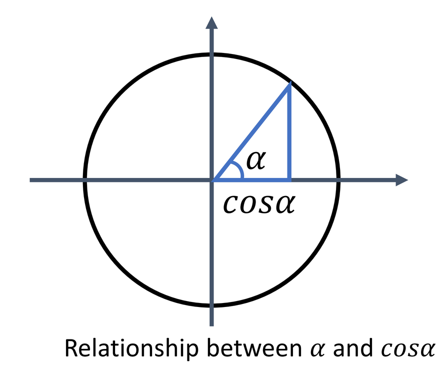
Weights of a DNN are stored in tensor which is H * C * W
Therefore, a tensor has three different decomposing ways.



Cosine Similarity

The **minimal intersecting angle** between w and t is equal to the maximum **cosine similarity** between them

$$\underset{t}{\operatorname{argmin}}\, \alpha = \underset{t}{\operatorname{argmax}} \frac{\boldsymbol{w}\cdot\boldsymbol{t}}{\|\boldsymbol{w}\|_2\|\boldsymbol{t}\|_2} = \underset{t}{\operatorname{argmax}} \frac{\widehat{\boldsymbol{w}}\cdot\boldsymbol{t}}{\|\boldsymbol{t}\|_2}$$



Relationship between α and $cos\alpha$

The maximum cosine similarity is decided by the ternary vector t, according to The dot product between a normalized w and a ternary vector

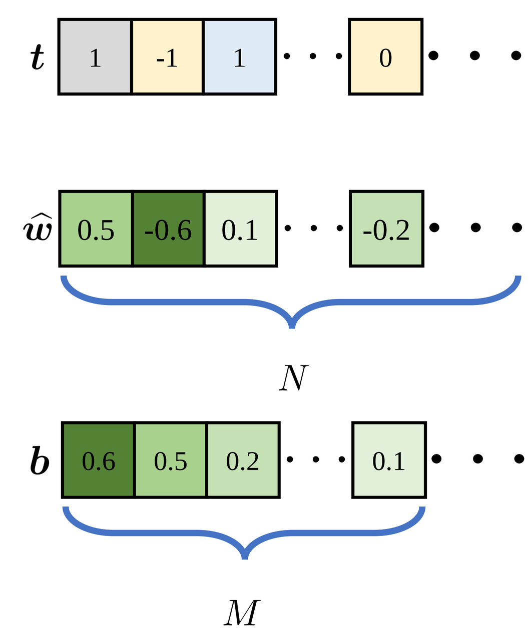
$$\underset{t}{\operatorname{argmax}} \frac{\widehat{\boldsymbol{w}}\cdot\boldsymbol{t}}{\|\boldsymbol{t}\|_2} = \underset{t_i}{\operatorname{argmax}} \frac{\sum_{i=1}^{N} a_i t_i}{\sqrt{\sum_{i=1}^{N}(t_i)^2}}$$

Sorting $|w_i|$in a decreasing order to obtain b, constraining the number of t, we have

$$\frac{\sum_{i=1}^{N} a_i t_i}{\sqrt{M}} \le \frac{\sum_{j=1}^{M} b_j}{\sqrt{M}}$$

Therefore, the searching range is only N, and the maximum cosine similarity is defined by

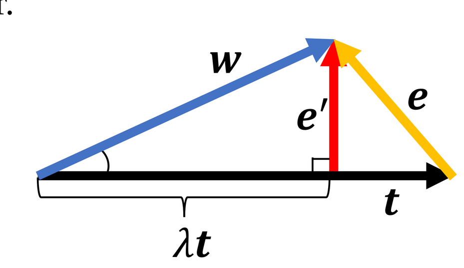
$$\operatorname{argmax}\left\{\frac{\sum_{i=1}^{M} b_i}{\sqrt{M}} \middle| M = 1, \ldots, N\right\}$$



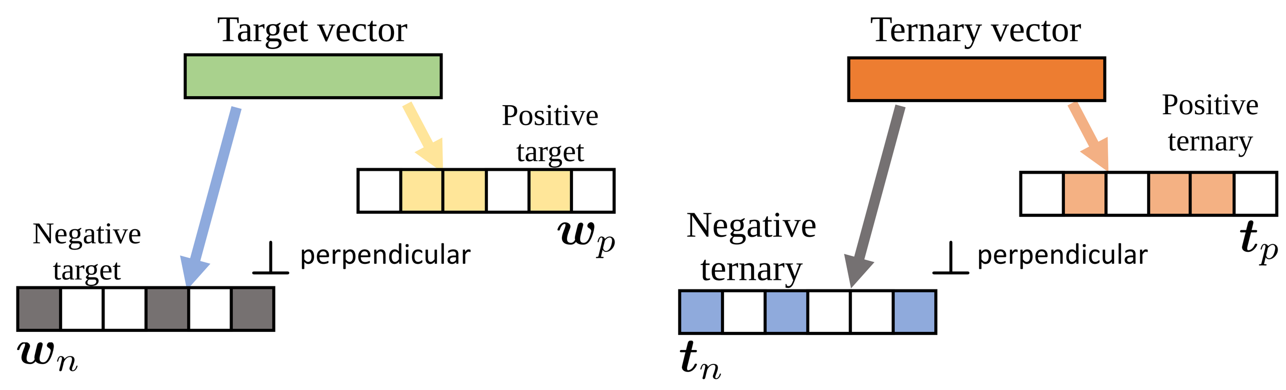
$$\frac{0.5+0.6+0.1+0}{\sqrt{3}} \le \frac{0.5+0.6+0.2+0}{\sqrt{3}}$$

Scalar-Tuning

- Introducing a scalar $\boldsymbol{\lambda}$, which can be obtained by orthogonal projection, to reduce the error further.



- Extracting the positive entries and negative entries from a target vector respectively to generate a positive vector and a negative vector.



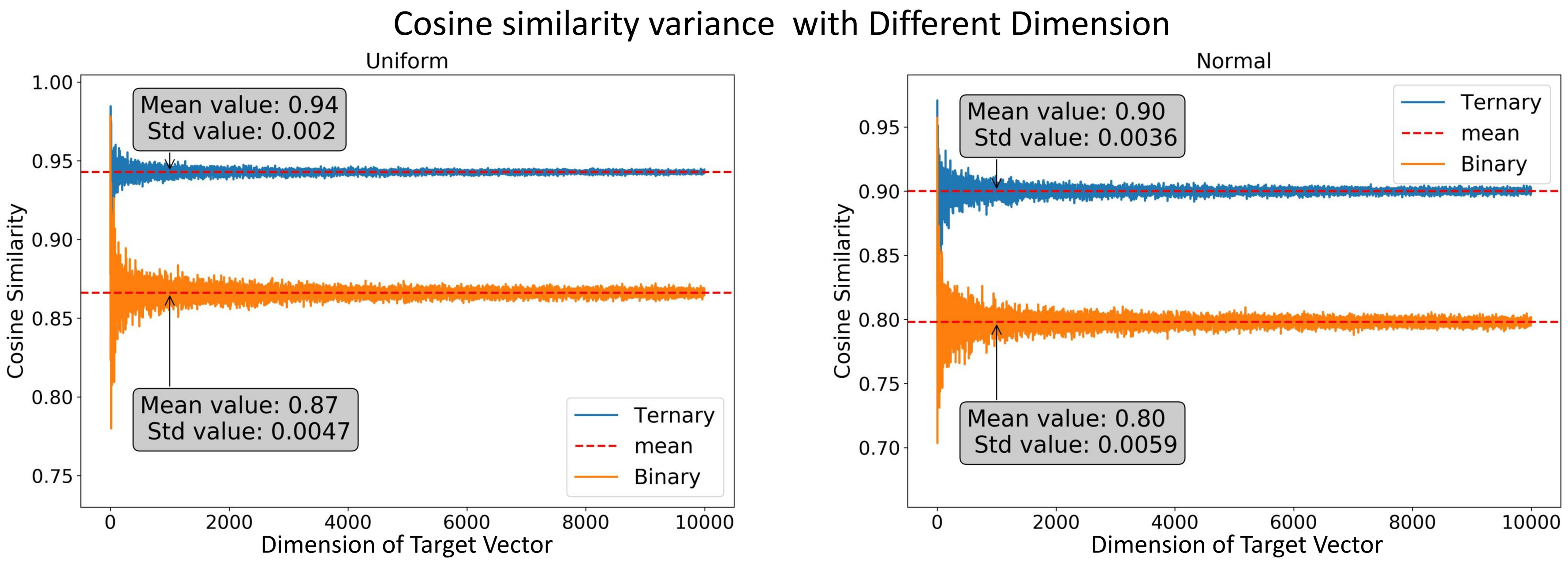
$$\left\|\boldsymbol{w} - \frac{\boldsymbol{w}\cdot\boldsymbol{t}}{\boldsymbol{t}\cdot\boldsymbol{t}}\boldsymbol{t}\right\|_2^2 \ge \left\|\boldsymbol{w}_p - \frac{\boldsymbol{w}_p\cdot\boldsymbol{t}_p}{\boldsymbol{t}_p\cdot\boldsymbol{t}_p}\boldsymbol{t}_p\right\|_2^2 + \left\|\boldsymbol{w}_n - \frac{\boldsymbol{w}_n\cdot\boldsymbol{t}_n}{\boldsymbol{t}_n\cdot\boldsymbol{t}_n}\boldsymbol{t}_n\right\|_2^2$$

- we can find **two scalars** that tuning positive and negative entries in ternary vector to reduce the error between target and ternary.

$$\lambda_p = \frac{\boldsymbol{w}_p\cdot\boldsymbol{t}_p}{\|\boldsymbol{t}_p\|} \qquad \lambda_n = \frac{\boldsymbol{w}_n\cdot\boldsymbol{t}_n}{\|\boldsymbol{t}_n\|}$$

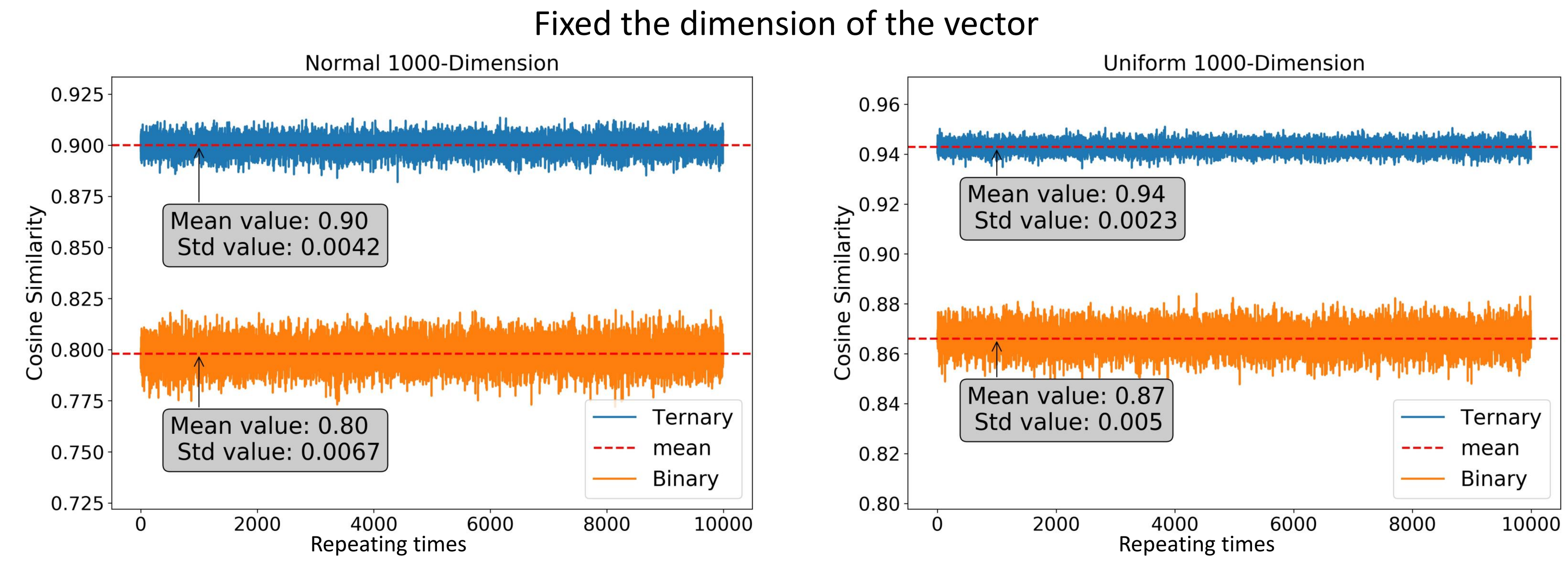
Simulation results

Cosine similarity variance with Different Dimension



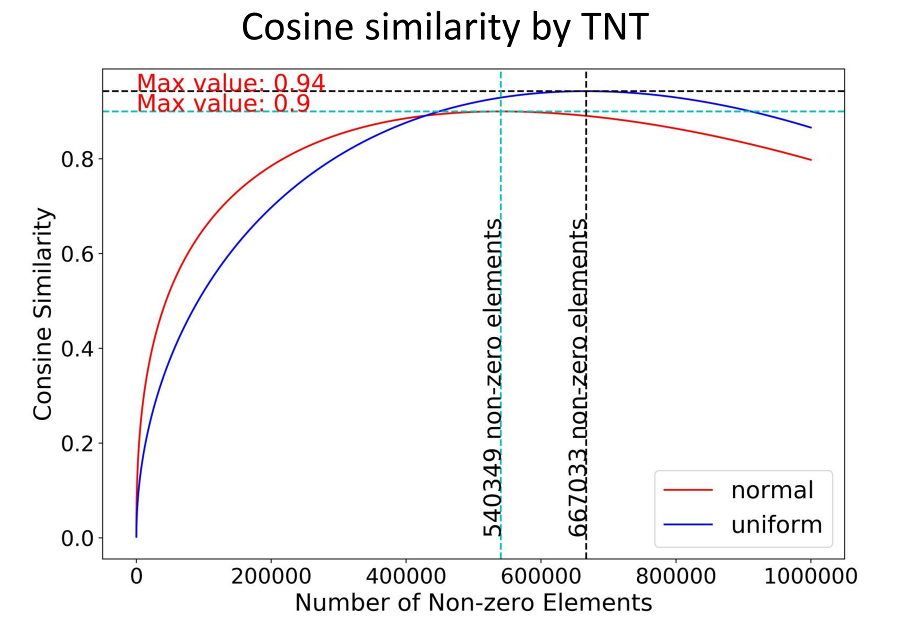
- With dimension increasing the cosine similarity becomes stable
- Uniform distribution has a higher similarity and lower variance

Fixed the dimension of the vector



The converting results is stable and uniform has a better results

Cosine similarity by TNT



- Normal distribution has a lower converting similarity
- Uniform distribution can have more zeros to reduce memory

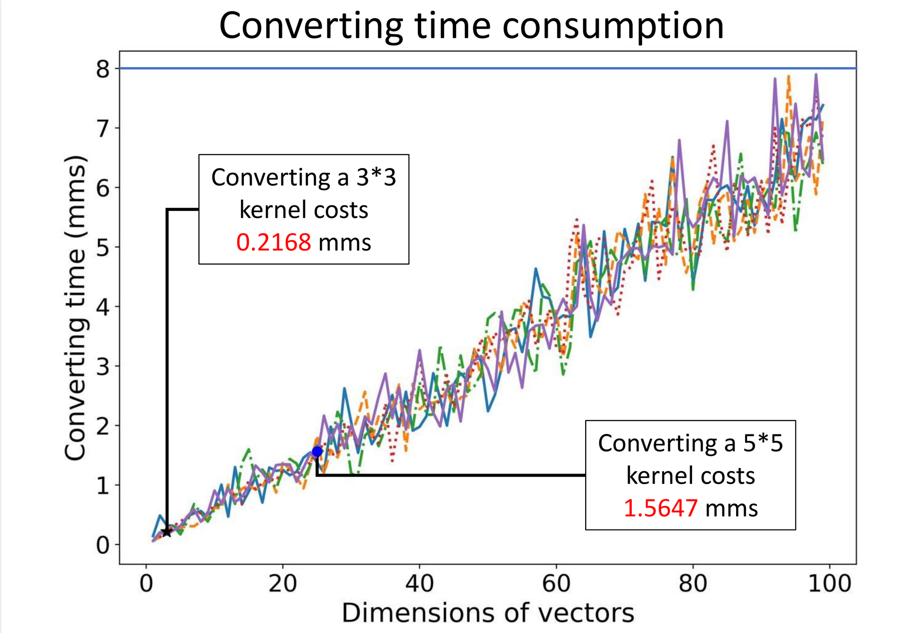
The Results on Converting Neural Network

Network	Base Line	TNT	parameter	Converting times
LeNet-5 (MNIST)	99.18%	98.97%	1,663,370	7.803s
VGG-7 (CIFAR-10)	91.31%	89.09%	7,734,410	88.288s
VGG-16 (ImageNet)	64.26%, 85.59%	56.26%, 80.25%	12,976,266	115.863s

Without retraining and fine-tuning

- LeNet-5 lost **0.21%** accuracy
- VGG-7 lost **2.22%** accuracy
- VGG-16 lost **5.34% Top-1** accuracy

Converting time consumption



- Converting 5 different vectors dimension from 1 to 100
- Converting a 100-D vector less than 8 mms

Contributions

TNT is an **efficient** parameters quantization method for neural network. According to this research we approached the following Contributions:

1. Reducing the searching range from 3^N to N
2. Constricting the searching time in **Nlog(N)**
3. Guaranteeing the best ternary vectors can be found
4. Showing that the initial parameters have an obvious affection on the weight converting result

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