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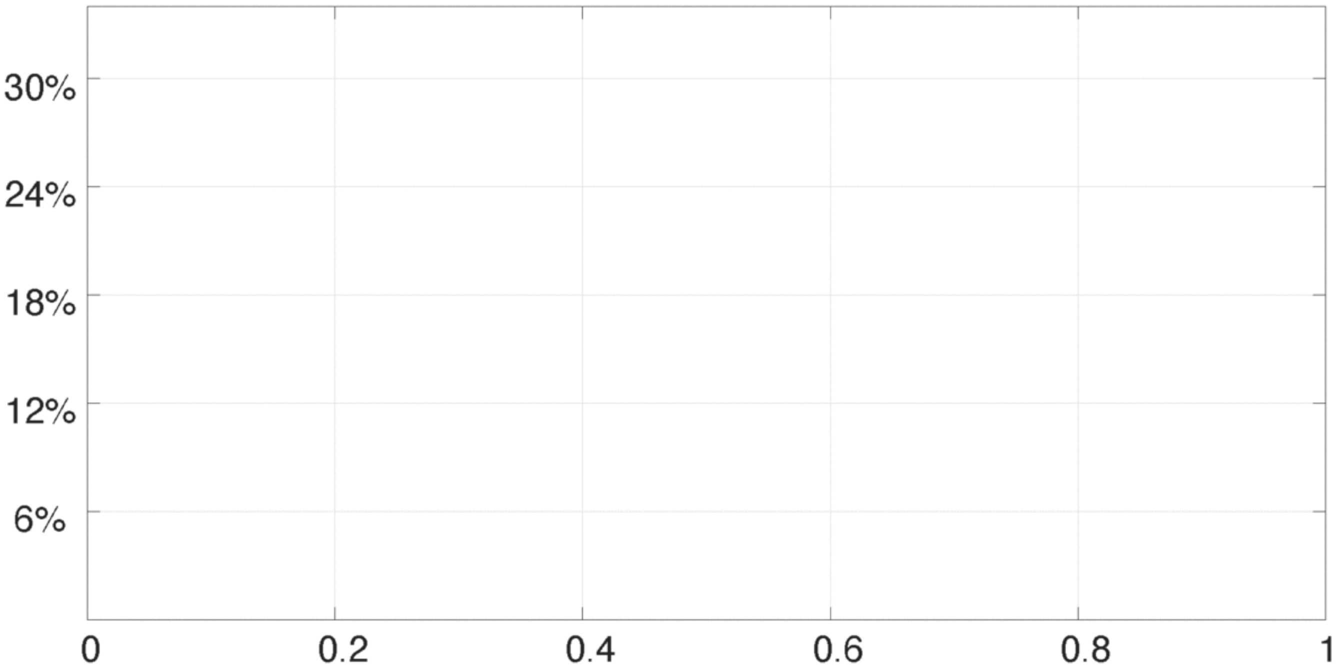
Orthogonal Convolutional Neural Networks

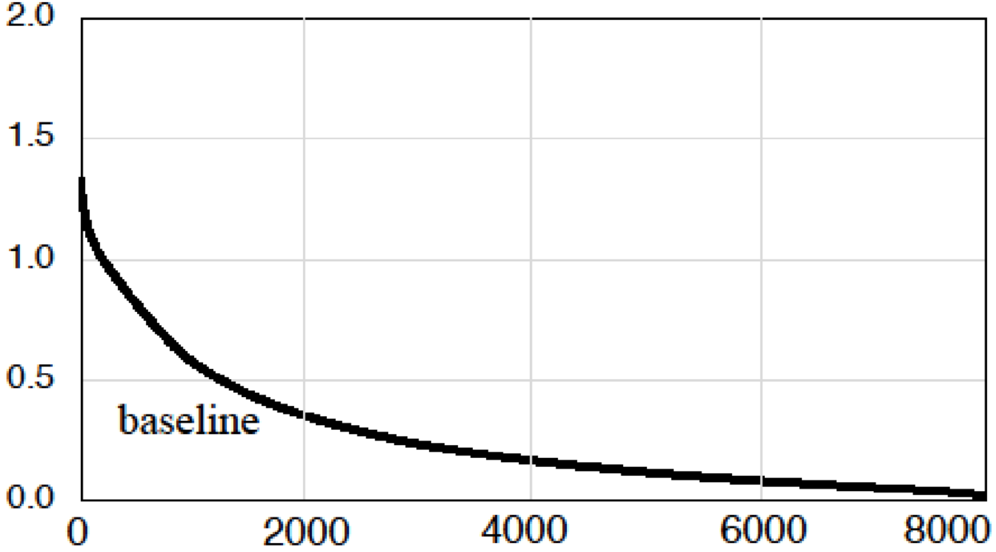
Jiayun Wang | Yubei Chen | Rudrasis Chakraborty | Stella X. Yu



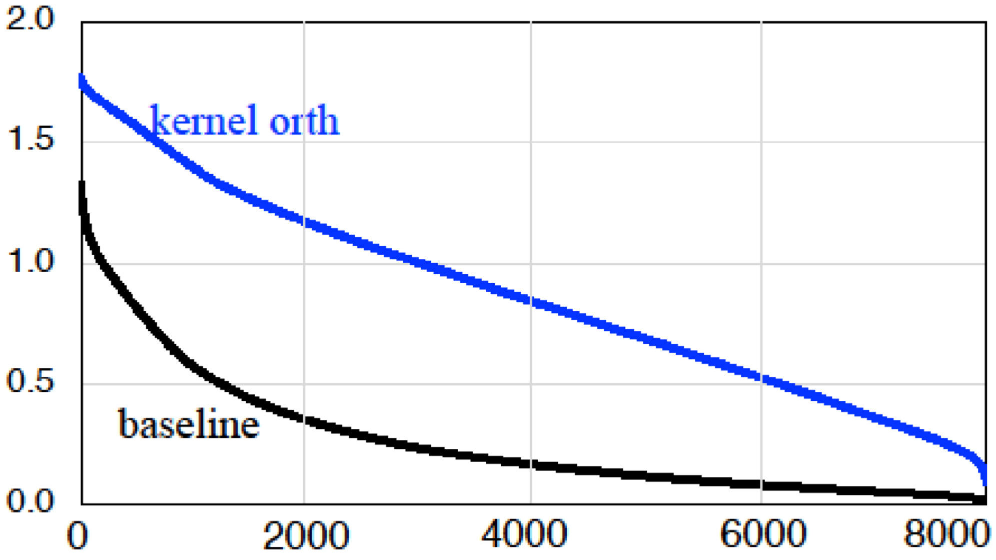

Filter similarity increases with depth



A typical conv layer has highly irregular spectrum



Kernel orthogonality is widely used as a regularization



Saxe et al. 2014

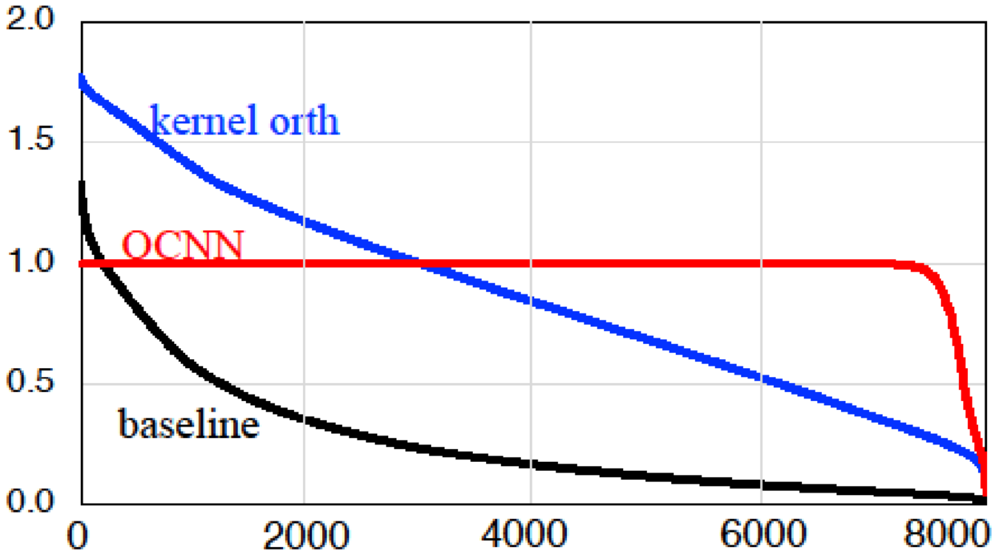
Dorobantu et al. 2016

Rodriguez et al. 2017

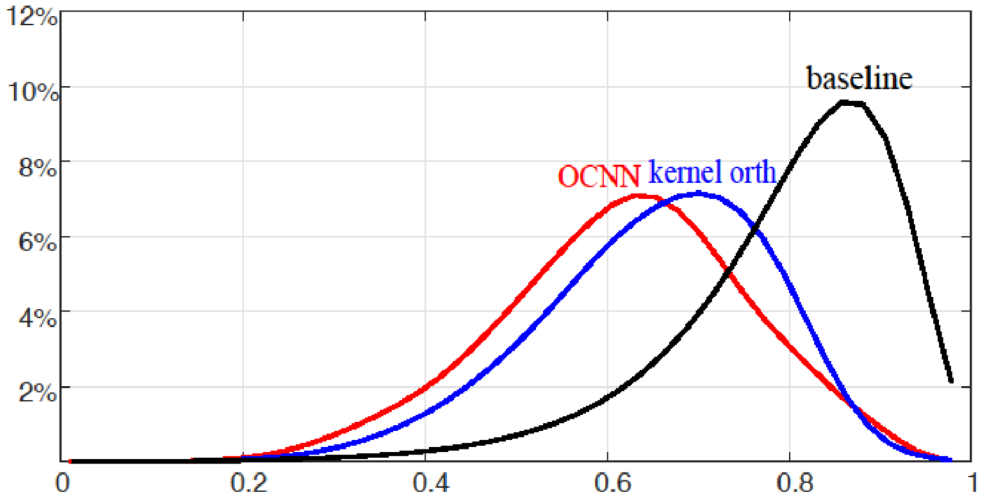
Bansal et al. 2018

...

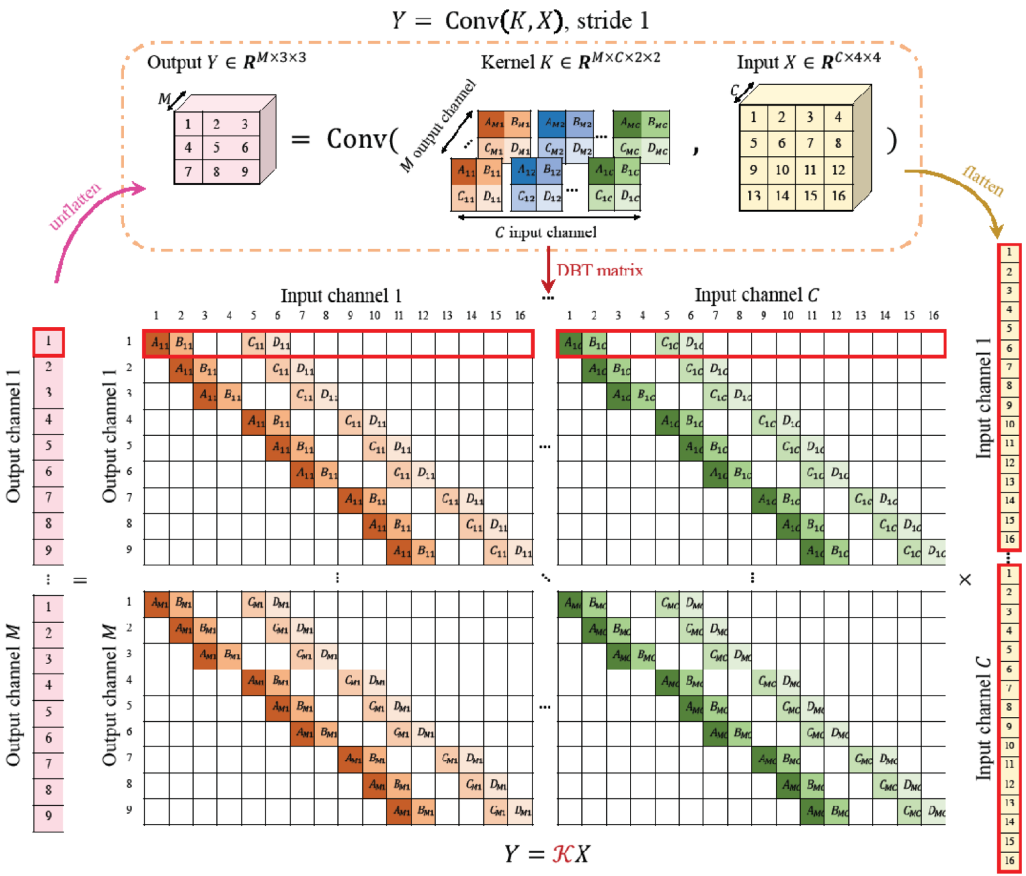
OCNN can do even better



Filter diversity improvement with OCNN



Convolution is an efficient matrix-vector multiplication



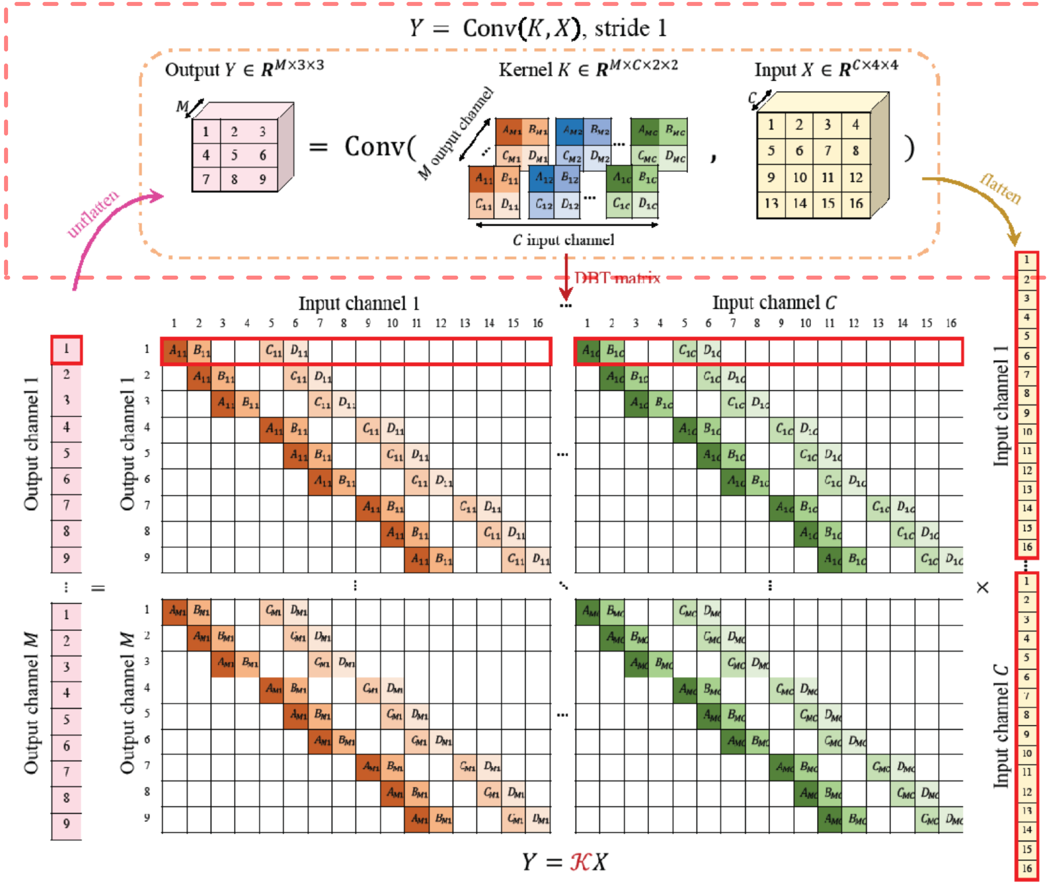
Convolution:

$$Y = K * X$$

Matrix-vector form:

$$K \to \textcolor{red}{\mathcal{K}}, Y = \textcolor{red}{\mathcal{K}}X$$

Convolution is an efficient matrix-vector multiplication



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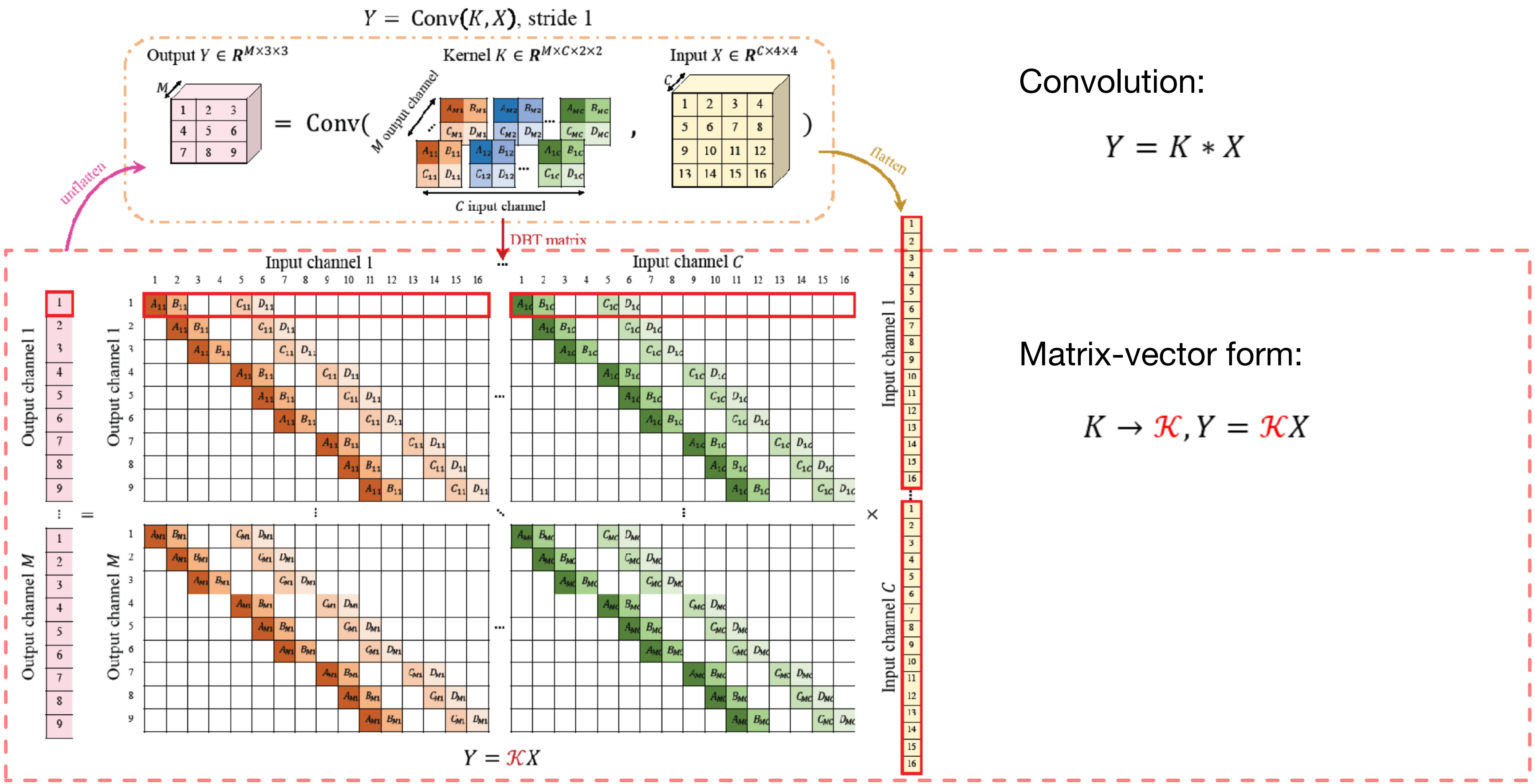

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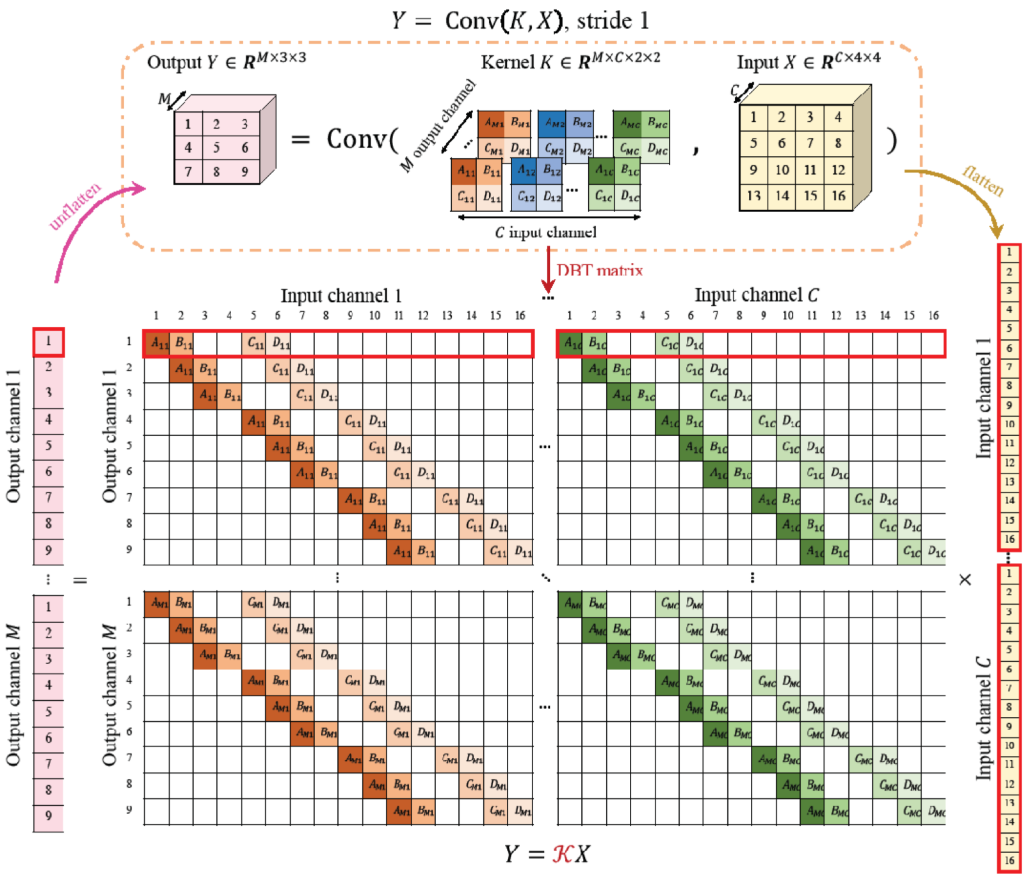
Orthogonal convolution or orthogonal kernel?



Convolution:

$$Y = K * X$$

kernel orthogonality: $KK^T = I$

Matrix-vector form:

$$K \to \mathcal{K} \quad Y = \mathcal{K}X$$

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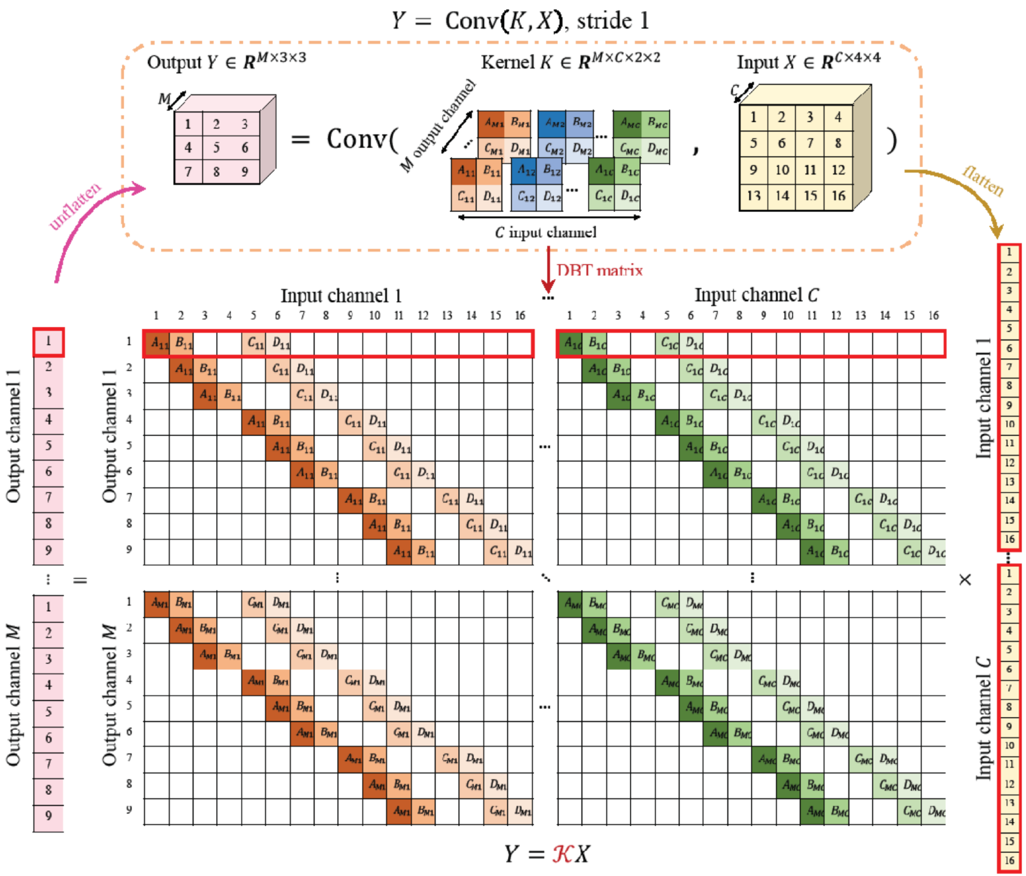

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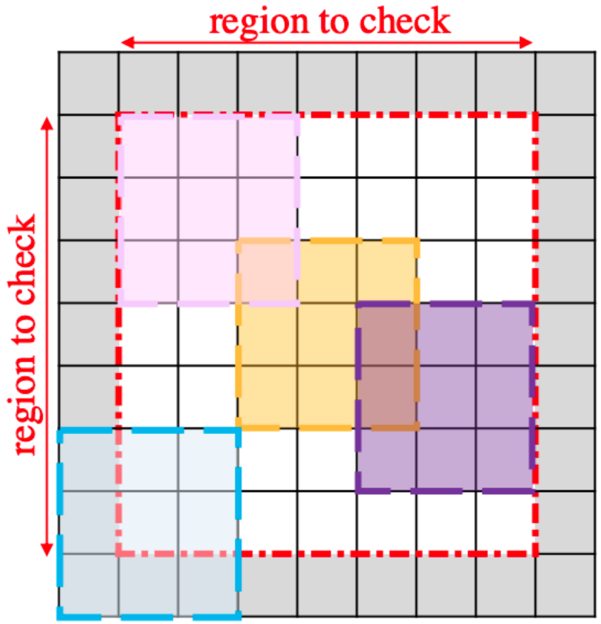
$$\mathcal{K}\mathcal{K}^T = I \Rightarrow KK^T = I$$

$$\mathcal{K}\mathcal{K}^T = I \not\Leftarrow KK^T = I$$

A fast algorithm for orthogonal convolution



- Kernel Orthogonality:

$$\begin{cases} \text{Conv}(K, K, \text{padding} = 0) = I_{r0} \\ \text{Conv}(K^T, K^T, \text{padding} = 0) = I_{c0} \end{cases}$$

- Convolutional Orthogonality:

$$\text{Conv}(K, K, \text{padding} = P, \text{stride} = S) = I_{r0}$$

Same # parameters and test time, only 9% more training time

Universal improvements

Task		Metric	Gain
Image Classificatio n	CIFAR100	classification accuracy	3%
	ImageNet	classification accuracy	1%
	semi-supervised learning	classification accuracy	3%
Feature Quality	ine-grained image retrieval	kNN classification accuracy	3%
	unsupervised image inpainting	PSNR	4.3
	image generation	FID	1.3
	deep metric learning	NMI	1.2
Robustness	black box attack	attack time	7x less

Thanks