

## 22) Style Transfer

### Gram Matrix

- Gram Matrix is ② without  $n+1$  data-scaling factor & mean centering

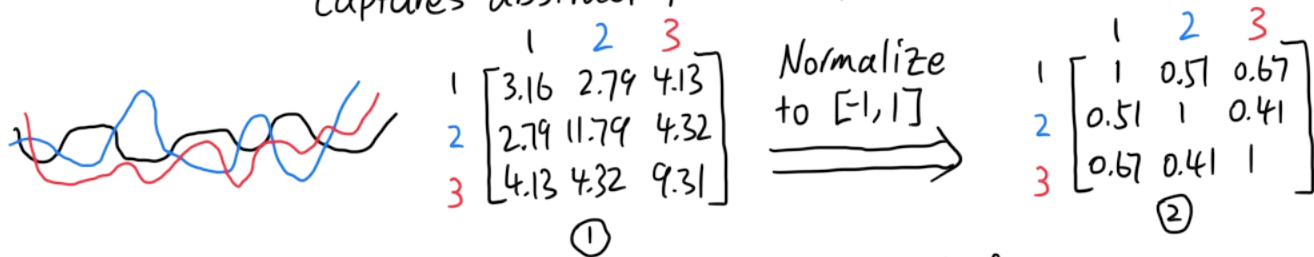
① Correlation: contains correlation coefficients b/t all pairs of the dataset features

• Formula:  $r_{x,y} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 (y_i - \bar{y})^2}}$

② Covariance: diagonal =  $\text{var}(\text{channel})$ , non-diagonal =  $\text{cov}(\text{channel A}, \text{channel B})$

• Formula:  $C_{x,y} = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})$

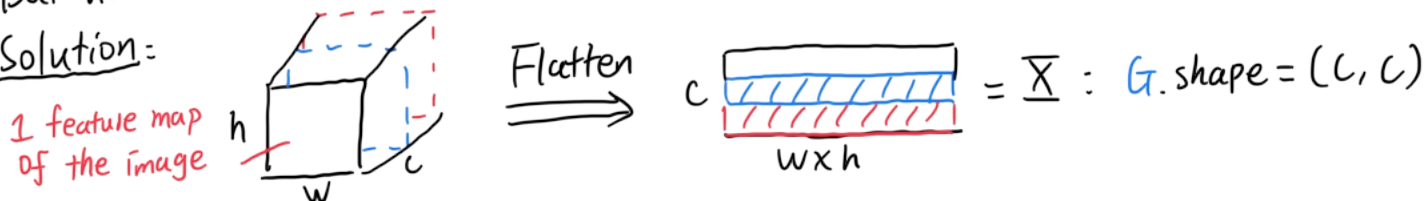
• Interpretation: represents all linear interactions across feature cols (for PCA) captures abstract patterns ('texture'/'style') of the image



- Gram Matrix:  $G = \bar{X}^T \bar{X}$ , where  $\bar{X}$  is pixels of 1 feature map

• But how to compute  $G$  for a convolution layer ( $>1$  feature maps)?

• Solution:



### Style Transfer Algorithm

- Overview: Content Image + Style Image = Target Image



$I = \text{Image}$   
 $G = \text{Gram matrix}$

- Steps:
- ① Initialize random  $\text{target } I$
  - ② Pick pretrained CNN network
  - ③ Match content in early layers ( $L_c = \text{MSE}(\text{target } I, \text{content } I)$ )
  - ④ Match style in convolution layers ( $L_s = \text{MSE}(\alpha_i (\text{target } G, \text{style } G))$ )
  - ⑤ Backprop  $\text{target } I$  on  $\text{Loss} = L_c + \beta L_s$

style scaling =  $1e6$

style weight for conv layer  $i$  decreasing as  $i$  gets higher