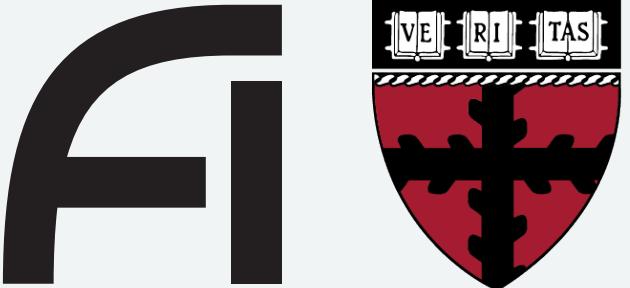


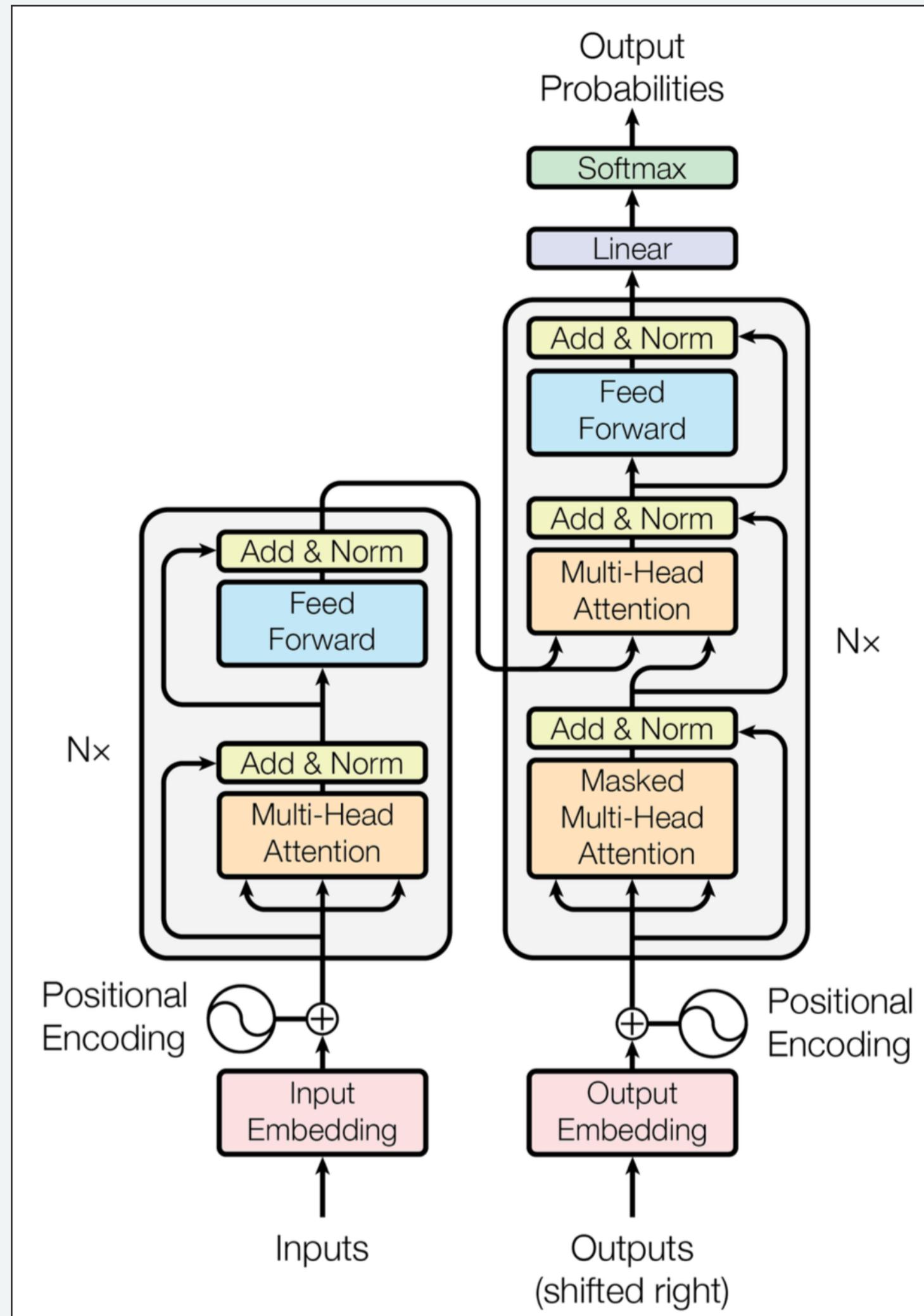
Learning ^{Cyclic} Linear Groups in Neural Networks

Friday, September 8, 2023

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Deep learning is empirical...



Transformer

Problems

- How to design?
- Functional understanding?
- Interpretability?

... and not very efficient



ChatGPT

- GPT-1 : 117M
- GPT-2 : 1.5B
- GPT-3 : 175B
- **GPT-4: 170T**

<https://chat.openai.com>



- LLaMA-2 7B : 7B
- LLaMA-2 13B : 13B
- **LLaMA-2 70B: 70B**

<https://ai.meta.com/llama/>



- LaMDA: 137B
- **PaLM : 540B**

<https://bard.google.com>



- **Claude 2: 175B**

<https://claude.ai/>

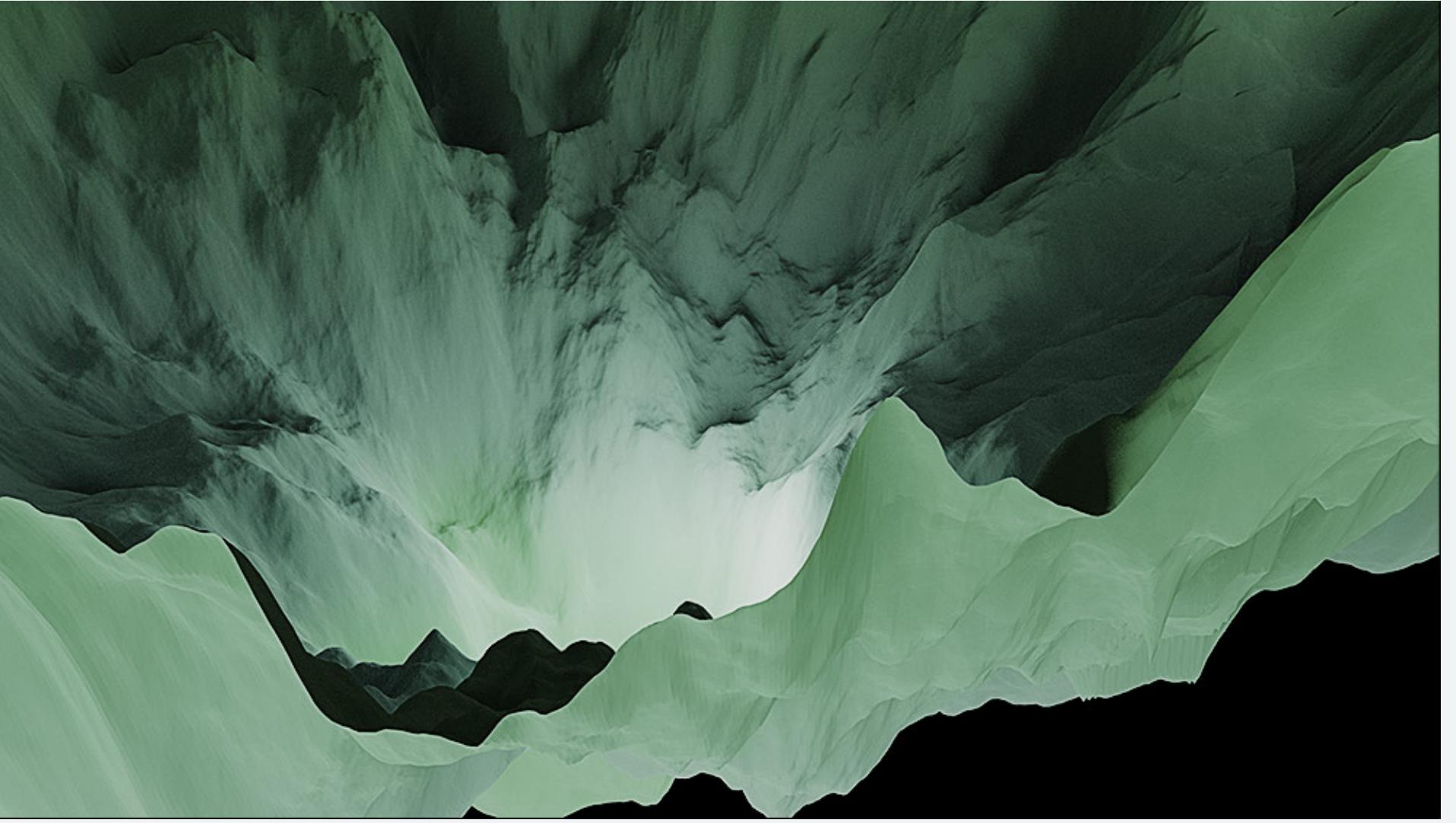


So?

Overparametrized models

- more parameters than data
- neurons memorize data points
- the rest interpolate

result: hope for the best.



Use domain knowledge

- in a systematic way
- constrain the parameter space

result: similar (or better!) performance and more efficient.

Enter equivariance

Classification has invariants

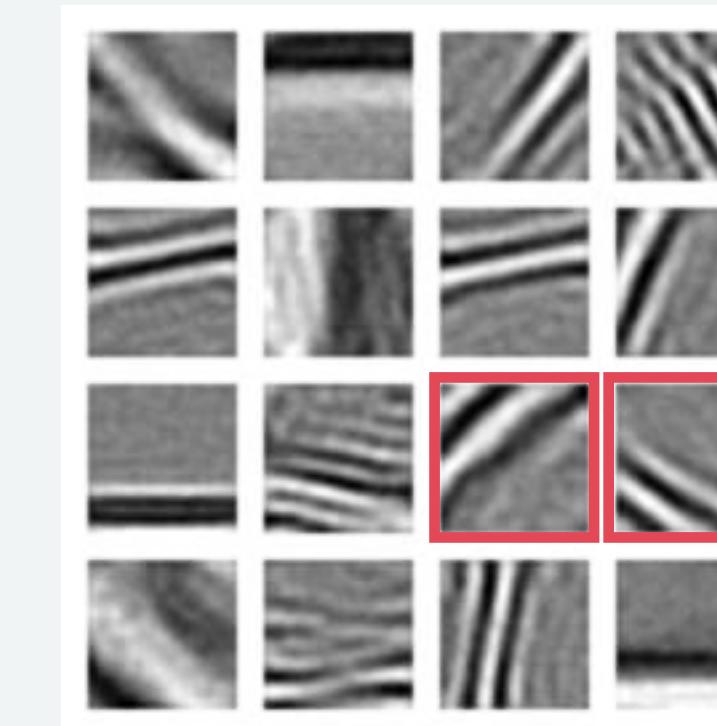


= Person on a chair



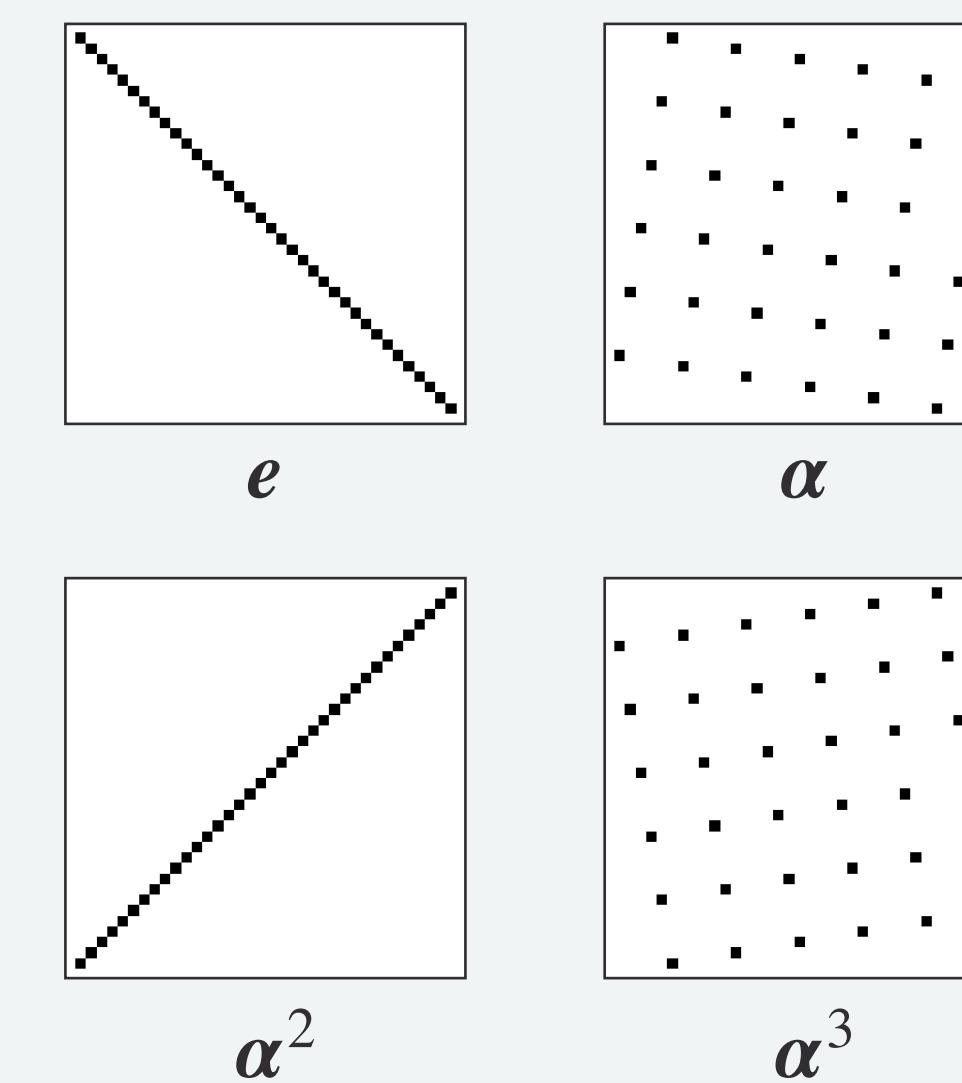
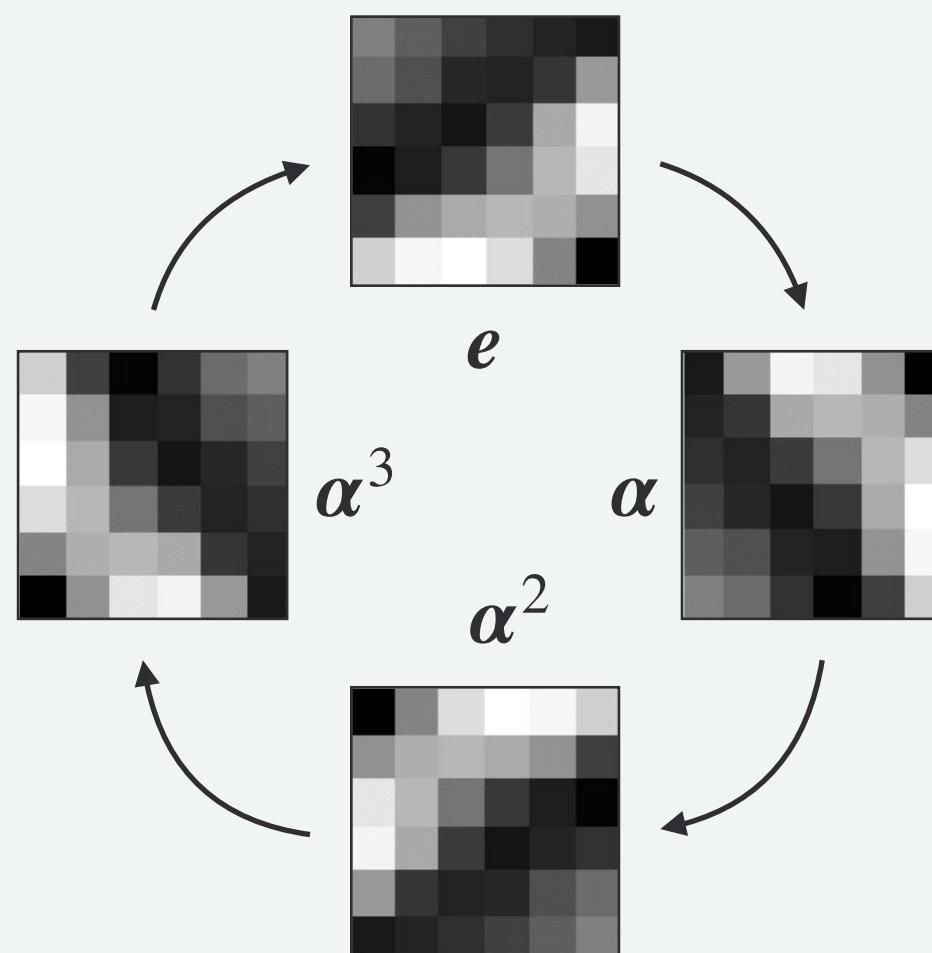
= Person on a chair

Filters have symmetries



different orientations

Group equivariant CNNs



How do we generalize?

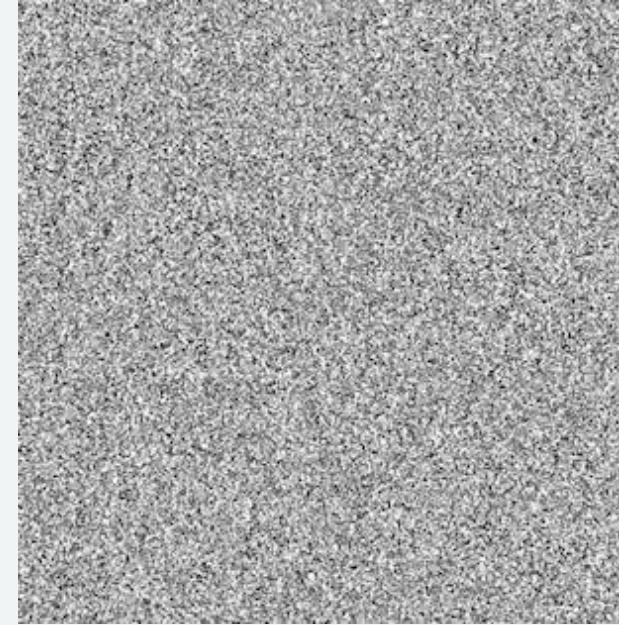
```
1  for i in range(10):  
2      print(i)  
3  
4
```

```
1  for i in range(10):  
2      rem = i % 10  
3      print(rem)  
4
```

code



privacy

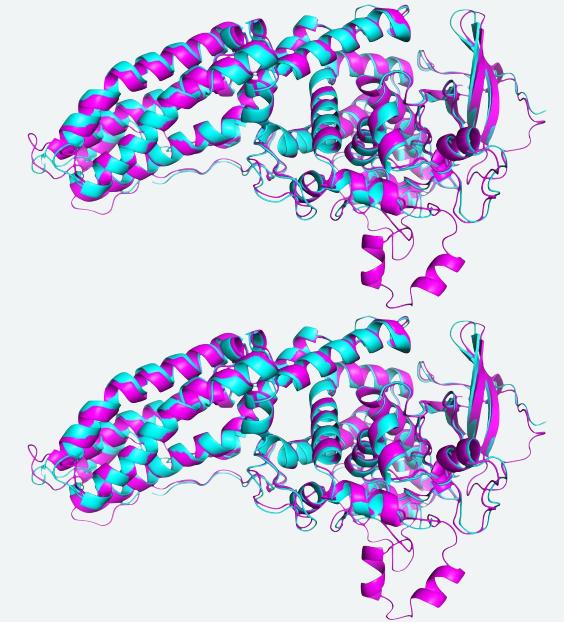


GCT
GCG

Alanine

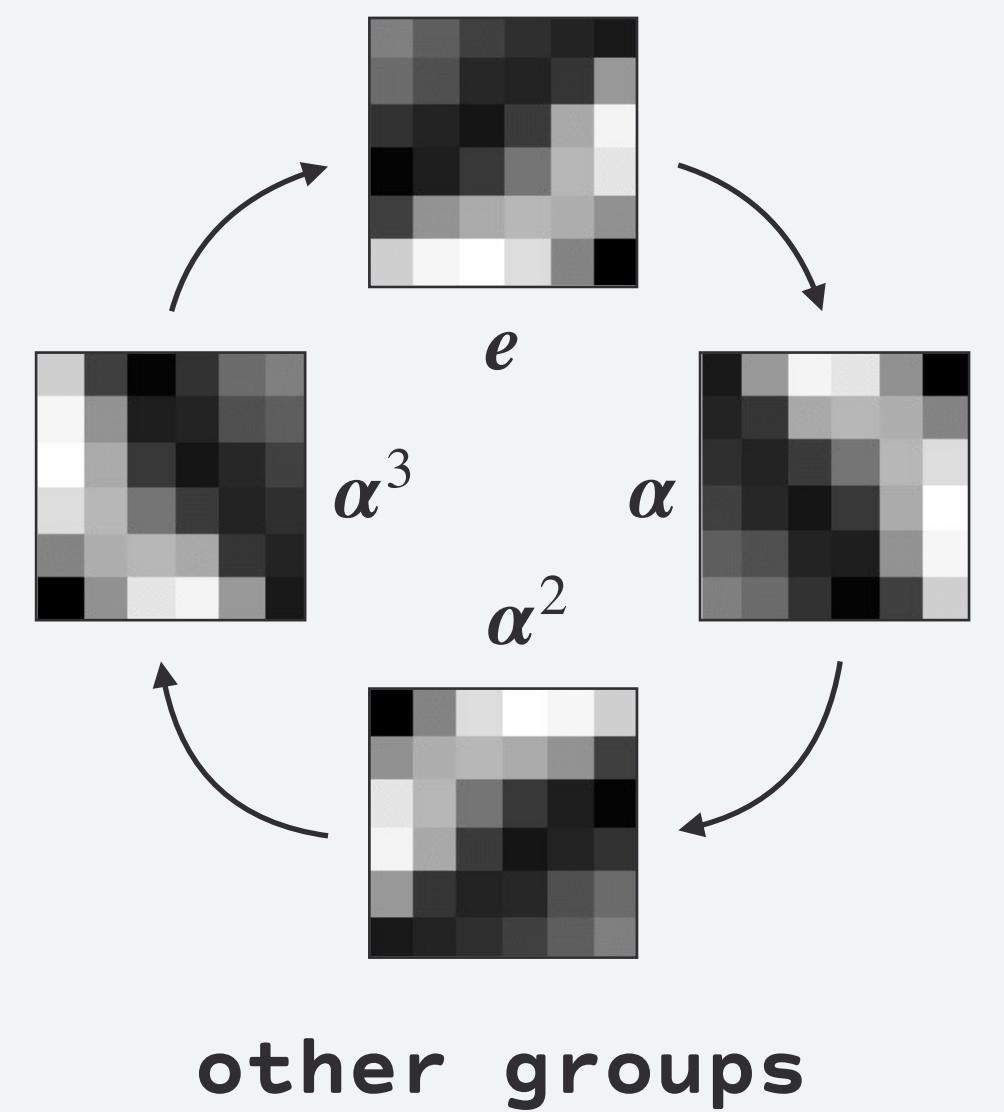
...AAT**GCT**ACT...

...AAT**GCG**ACT...

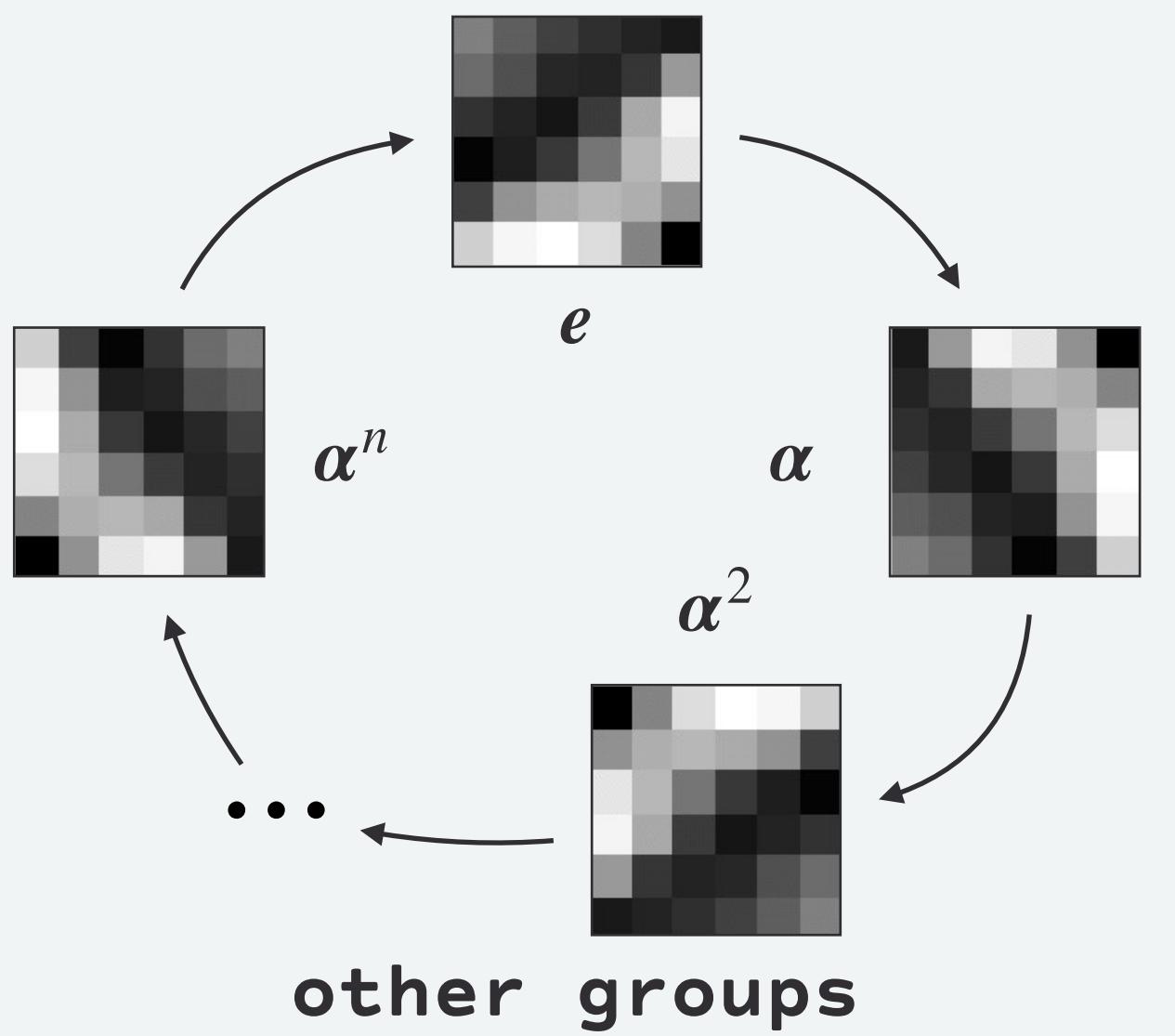


biology

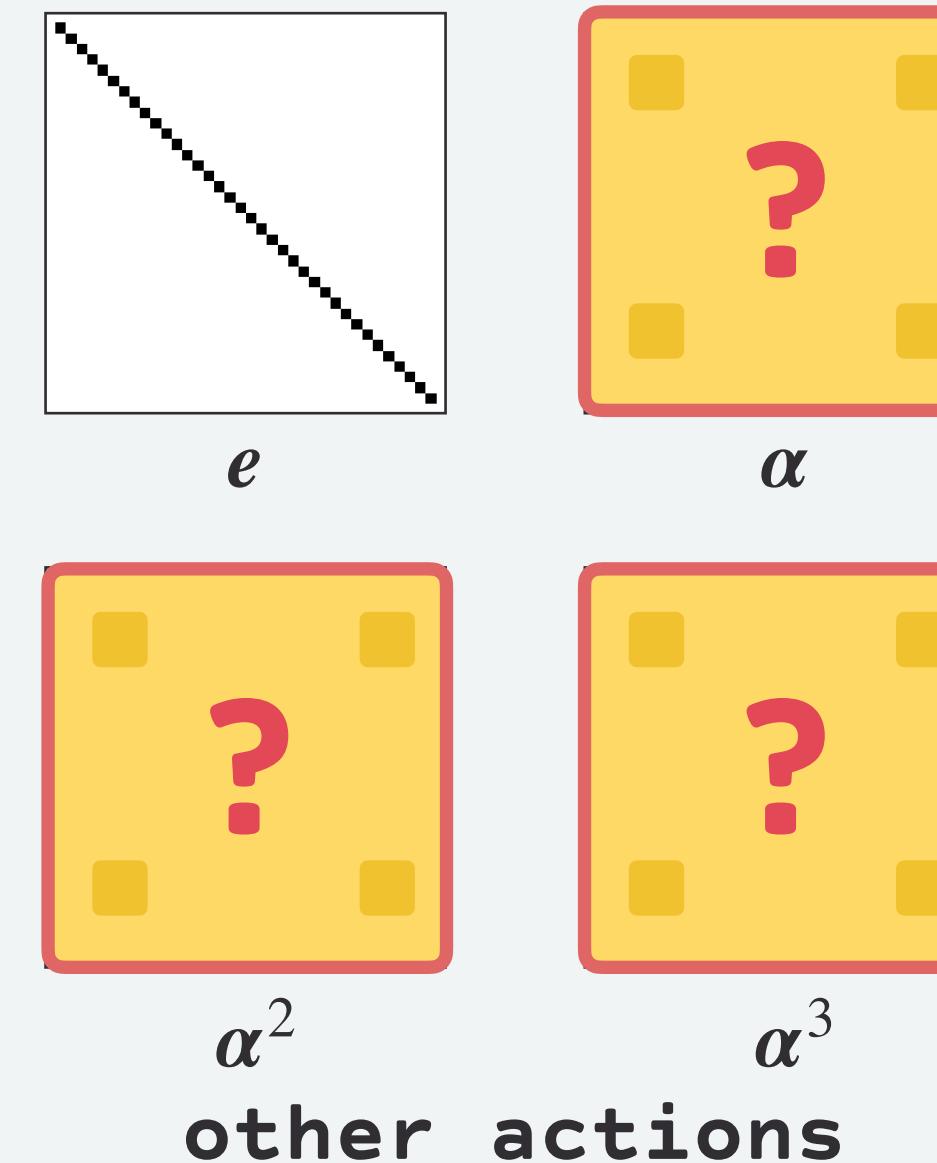
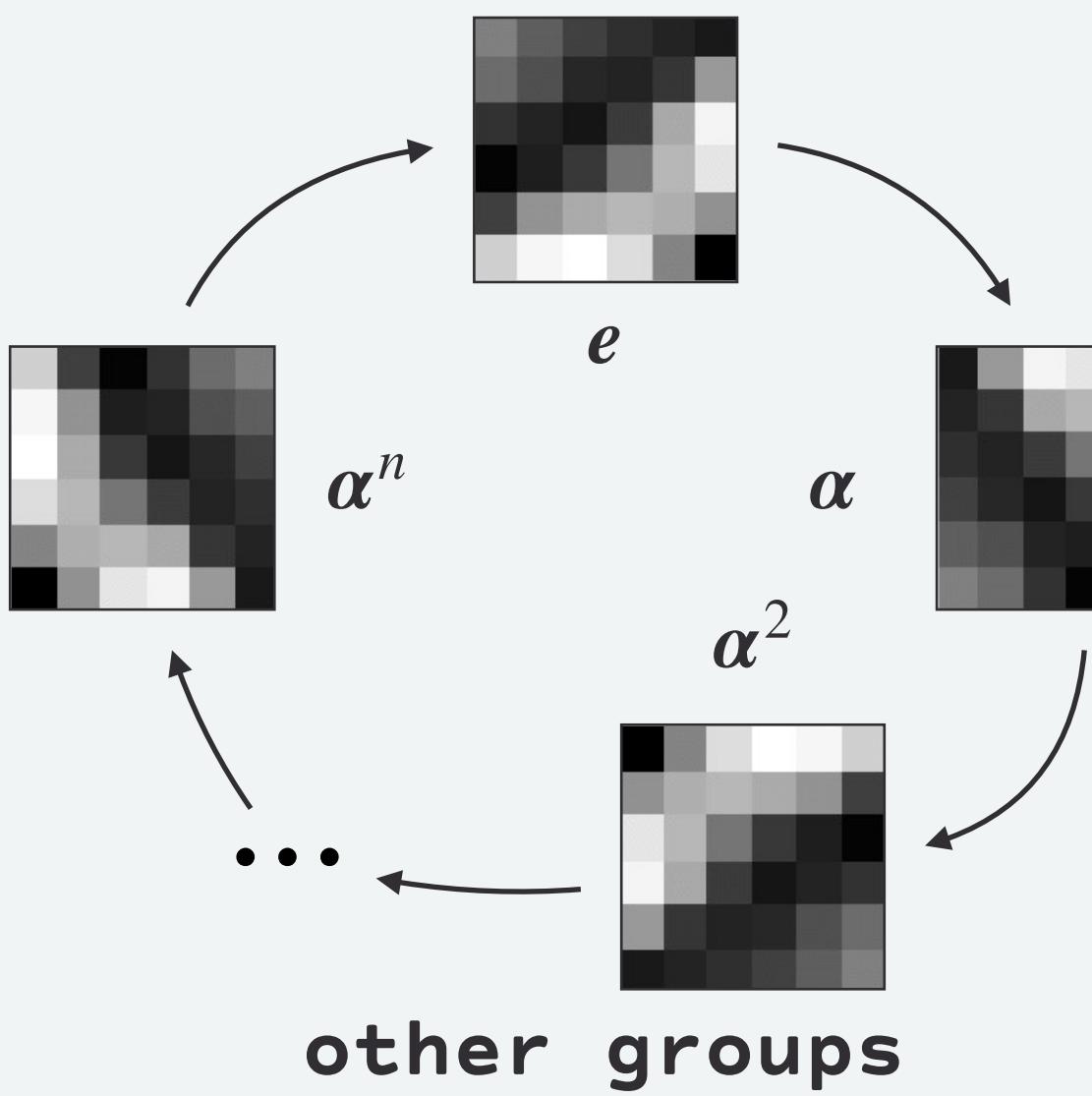
Our work



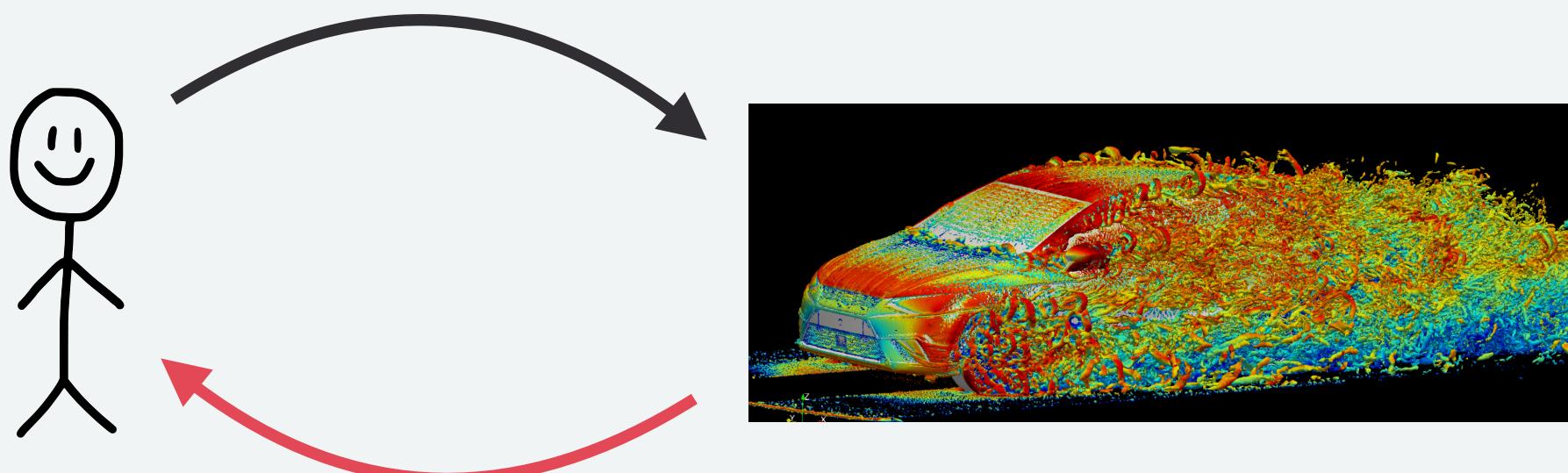
Our work



Our work



Benefits



bidirectional information flow

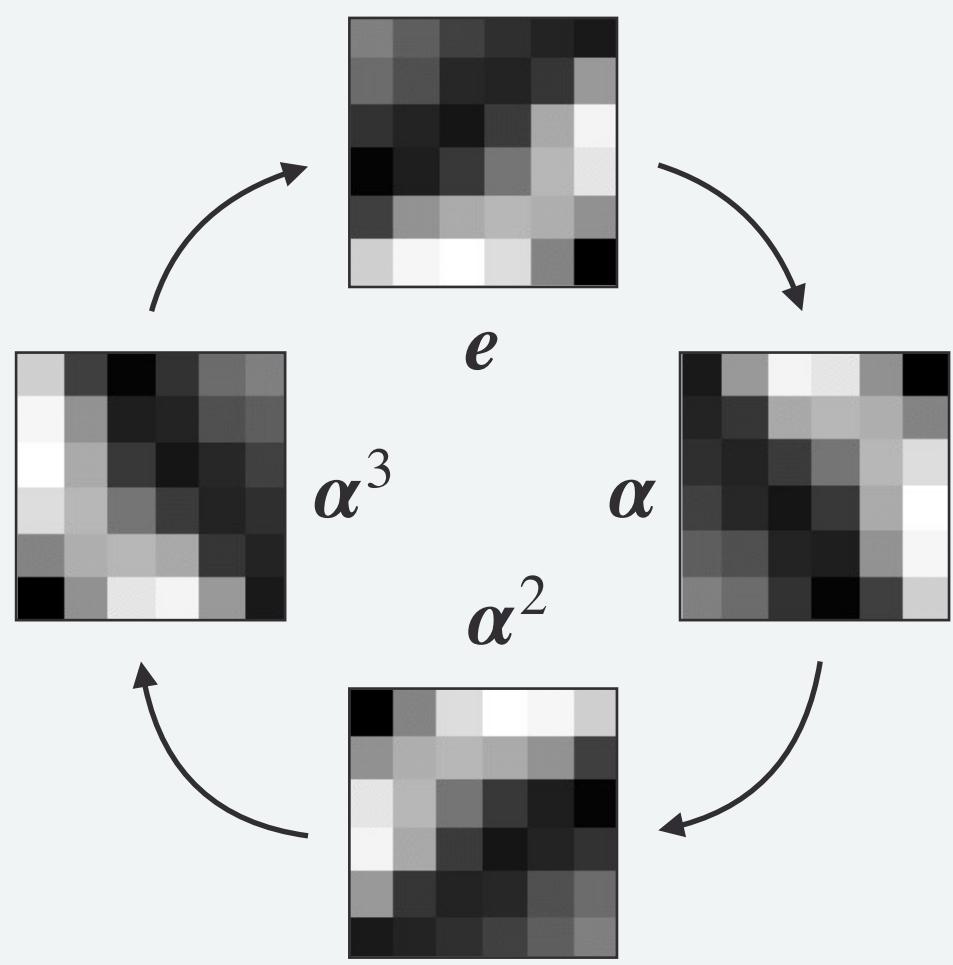


efficient models



Approach

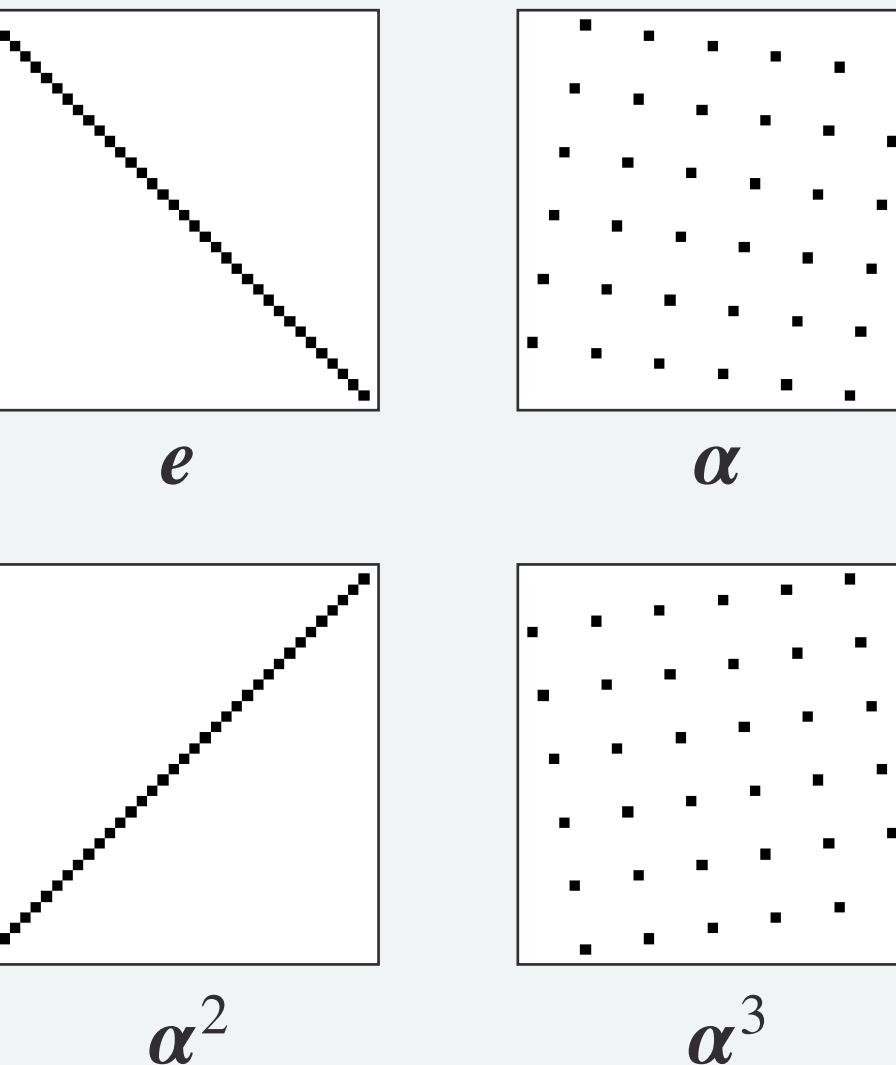
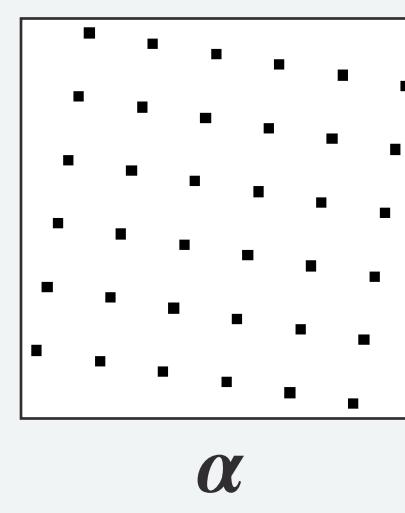
Elements of group theory



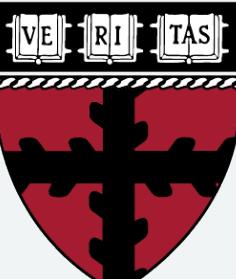
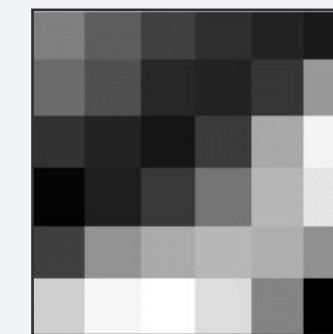
Abstract group
High level interactions

$$\{e, \alpha, \alpha^2, \alpha^3\}$$

Group representation
“Implementation” matrices



Data space
Where the group acts



Elements of group theory

Cyclic groups

What are they?

$$C_4 = \{e, \alpha, \alpha^2, \alpha^3\}$$

Why do we care?

- **short:** computation
- **long:** finite*, abelian, generator

$$T_{g_1}(\blacksquare) \ T_{g_2}(\blacksquare) \ \dots$$

$$\alpha^k \cdot \alpha^l = \alpha^l \cdot \alpha^k$$

$$T_g(\blacksquare) \ T_g(\blacksquare) \ \dots$$

Equivariance

What does it mean?

$$f(\curvearrowleft \circ \blacksquare) = \curvearrowright \circ f(\blacksquare)$$

(A bit more formally $f(T(x)) = T'(f(x))$.)

Example:

$$f(x) = x^2 \quad \text{vs}$$

$$f(\alpha \cdot x) = \alpha^2 \cdot x^2$$

Here $T(u) = \alpha \cdot u$ and $T'(u) = \alpha^2 \cdot u$.

So where do groups come in?

$$T = \begin{bmatrix} & & & \\ & \cdot & \cdot & \cdot \end{bmatrix}$$

$$T' = \begin{bmatrix} & & & \\ & \cdot & \cdot & \cdot \end{bmatrix}$$

Represent the “same” transformation!

Main idea

Theorem¹: For equivariance of a neural network with respect to a group G each layer needs to be a G -convolution.

$$(f * g)(u) = \sum_{v \in G} f(uv^{-1})g(v) \quad (\text{vs } (f * g)(u) = \sum_{v \in \mathbb{Z}} f(u - v)g(v))$$

For C_4

Convolution with the rotated set

What about C_n ?

Cardinality and action change

$$\left[\begin{array}{c} \text{Image 1} \\ \text{Image 2} \\ \text{Image 3} \\ \text{Image 4} \end{array} \right]$$

$$\left[\begin{array}{cccc} \text{[Image]} & g(\text{[Image]}) & \cdots & g^{n-1}(\text{[Image]}) \end{array} \right]$$

How to represent g ?

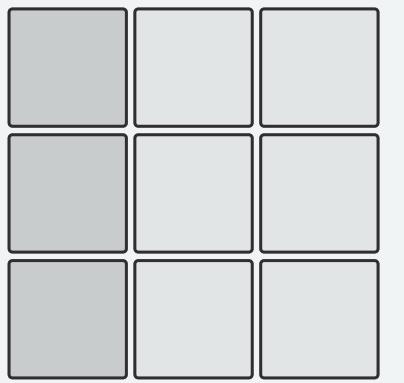
Use invertible matrices

$$\rho : G \rightarrow \mathrm{GL}_d(\mathbb{R})$$

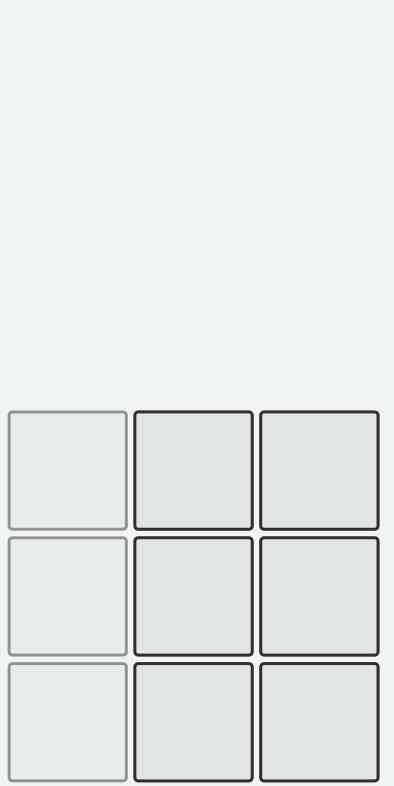
$$g = A =$$


$$\left[\begin{array}{cccc} \text{matrix} & A & \text{matrix} & \cdots & A^{n-1} & \text{matrix} \end{array} \right]$$

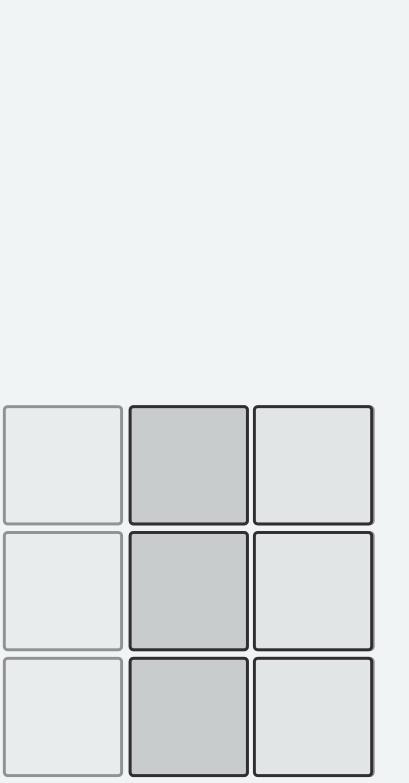
Vectorization



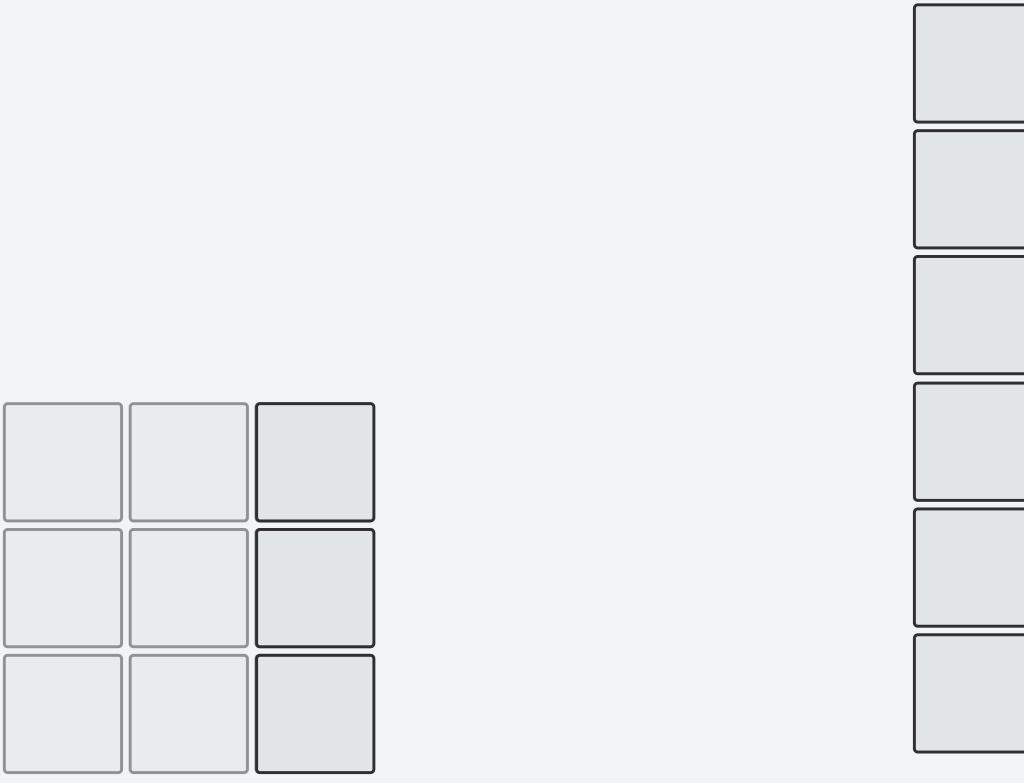
Vectorization



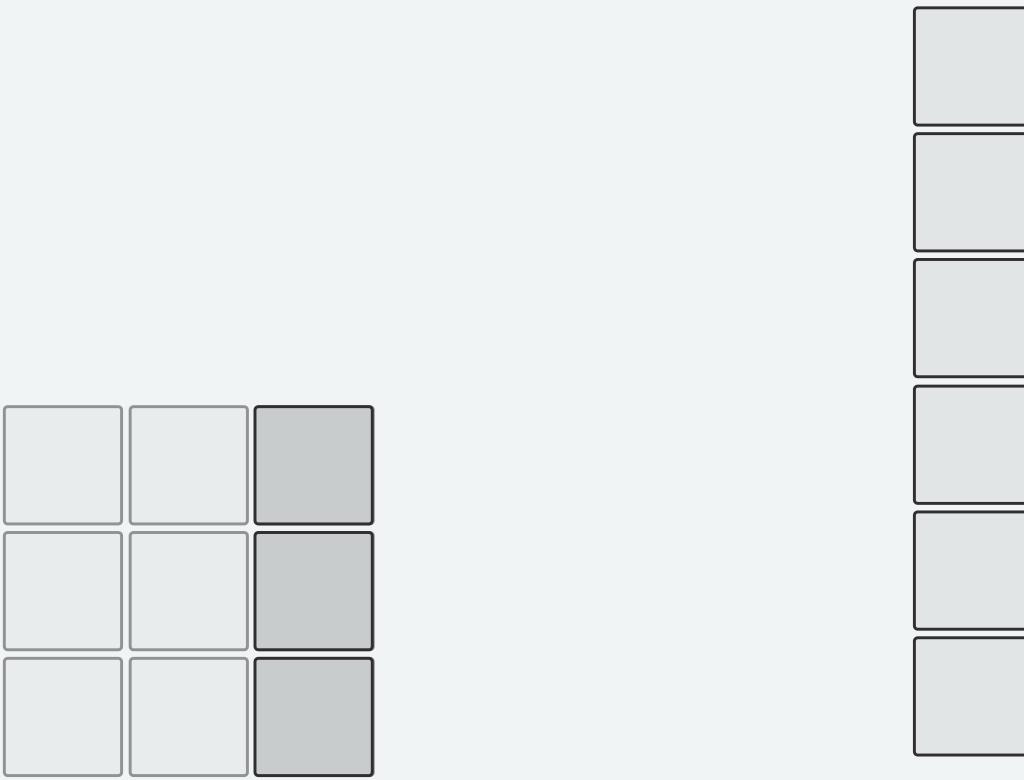
Vectorization



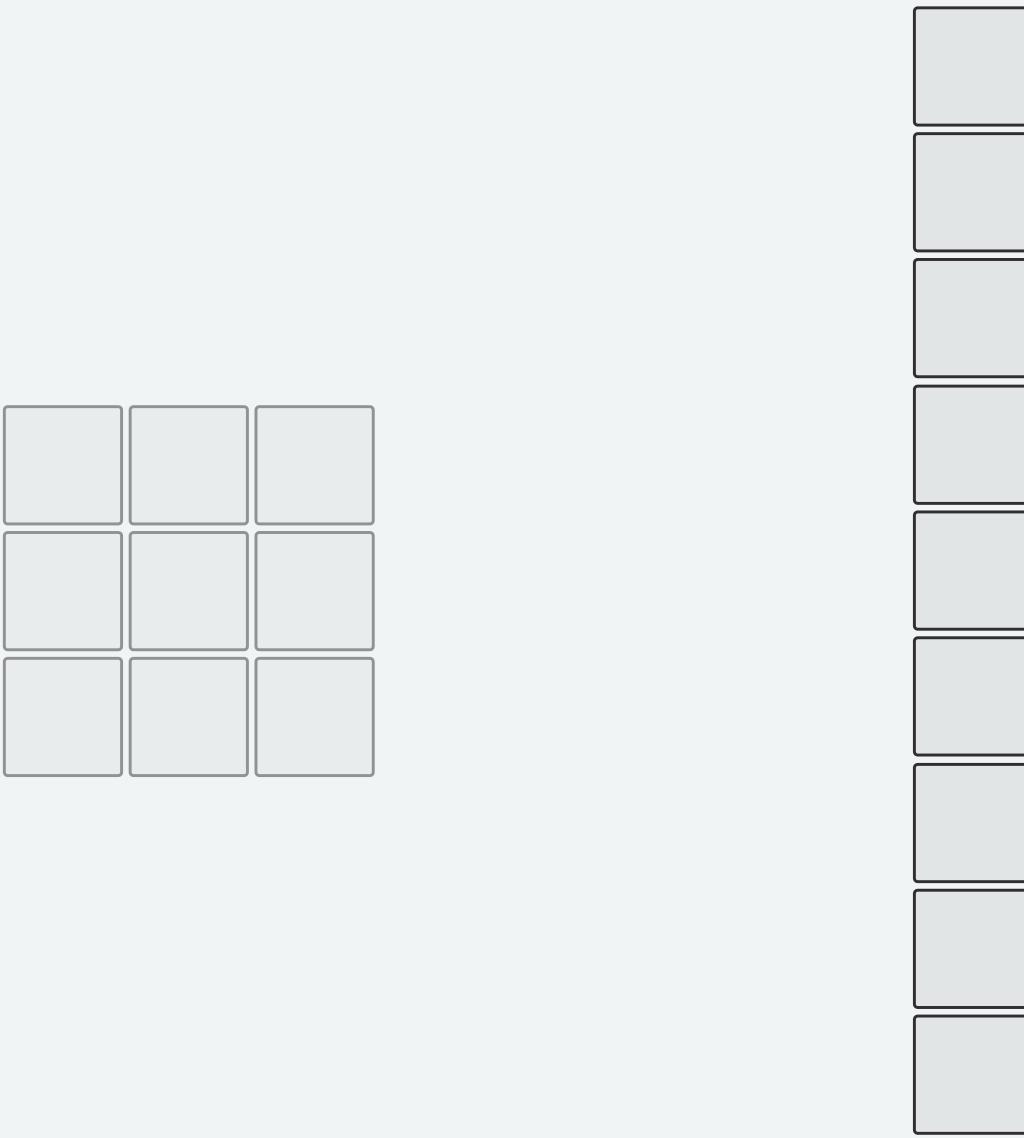
Vectorization



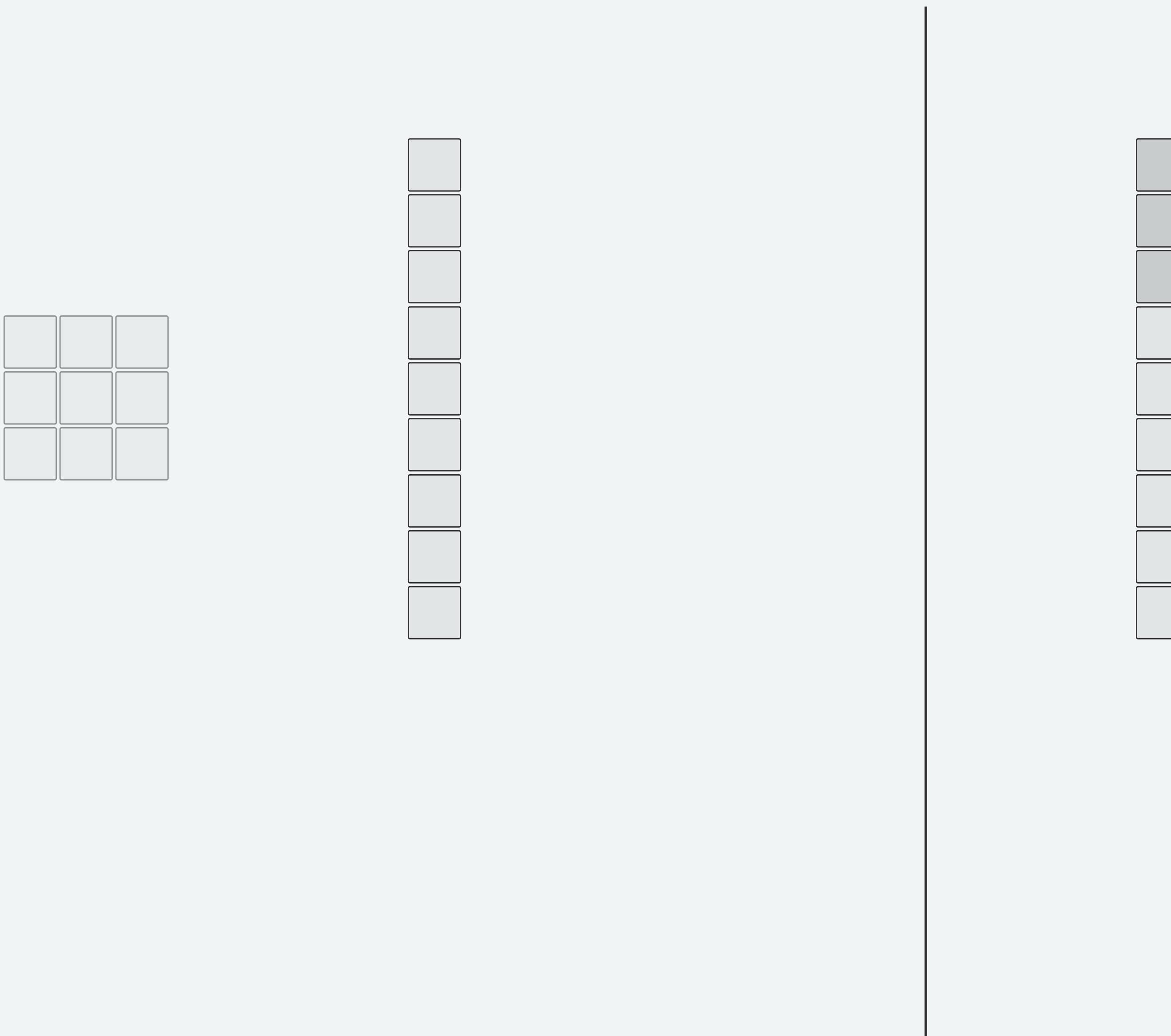
Vectorization



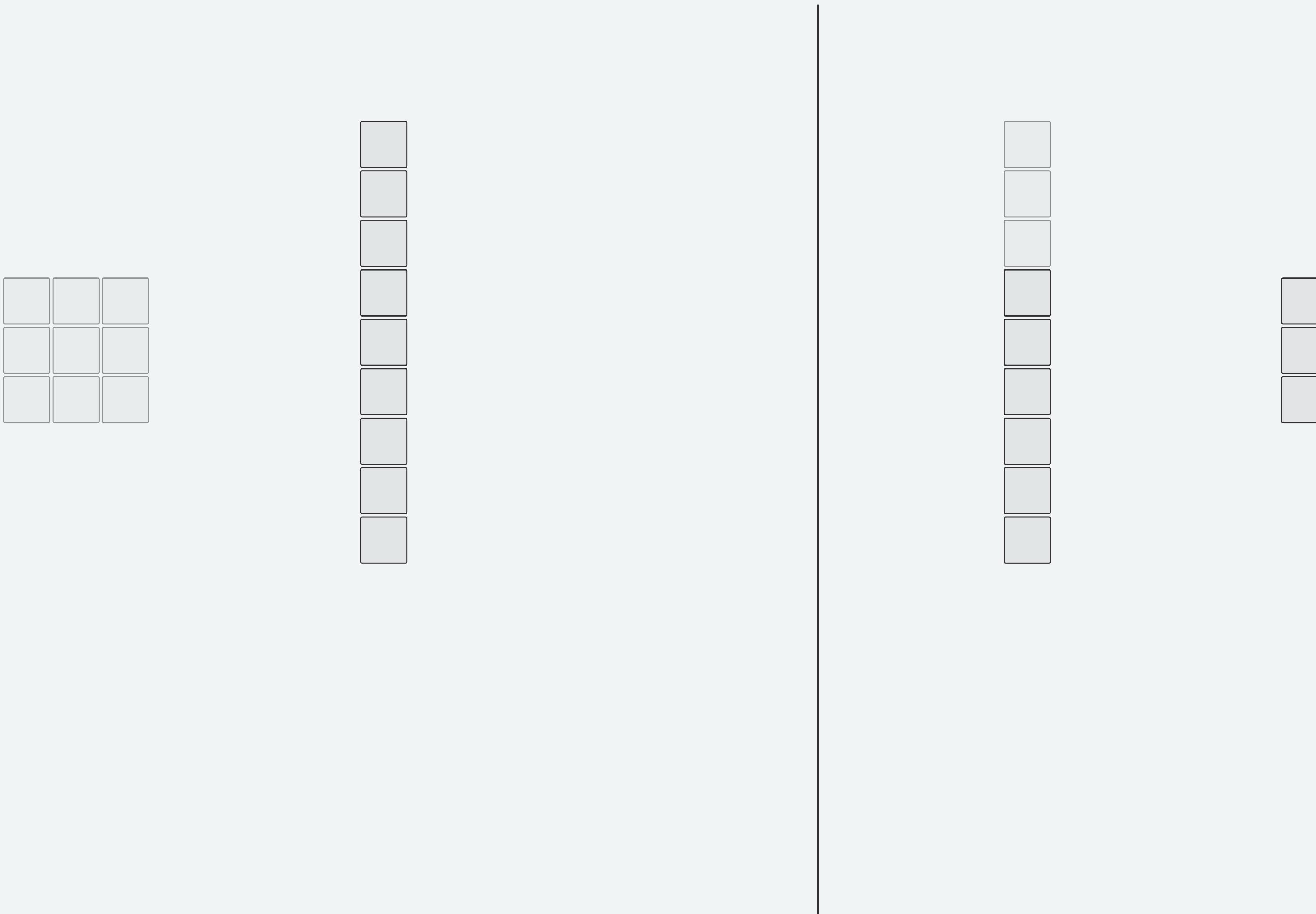
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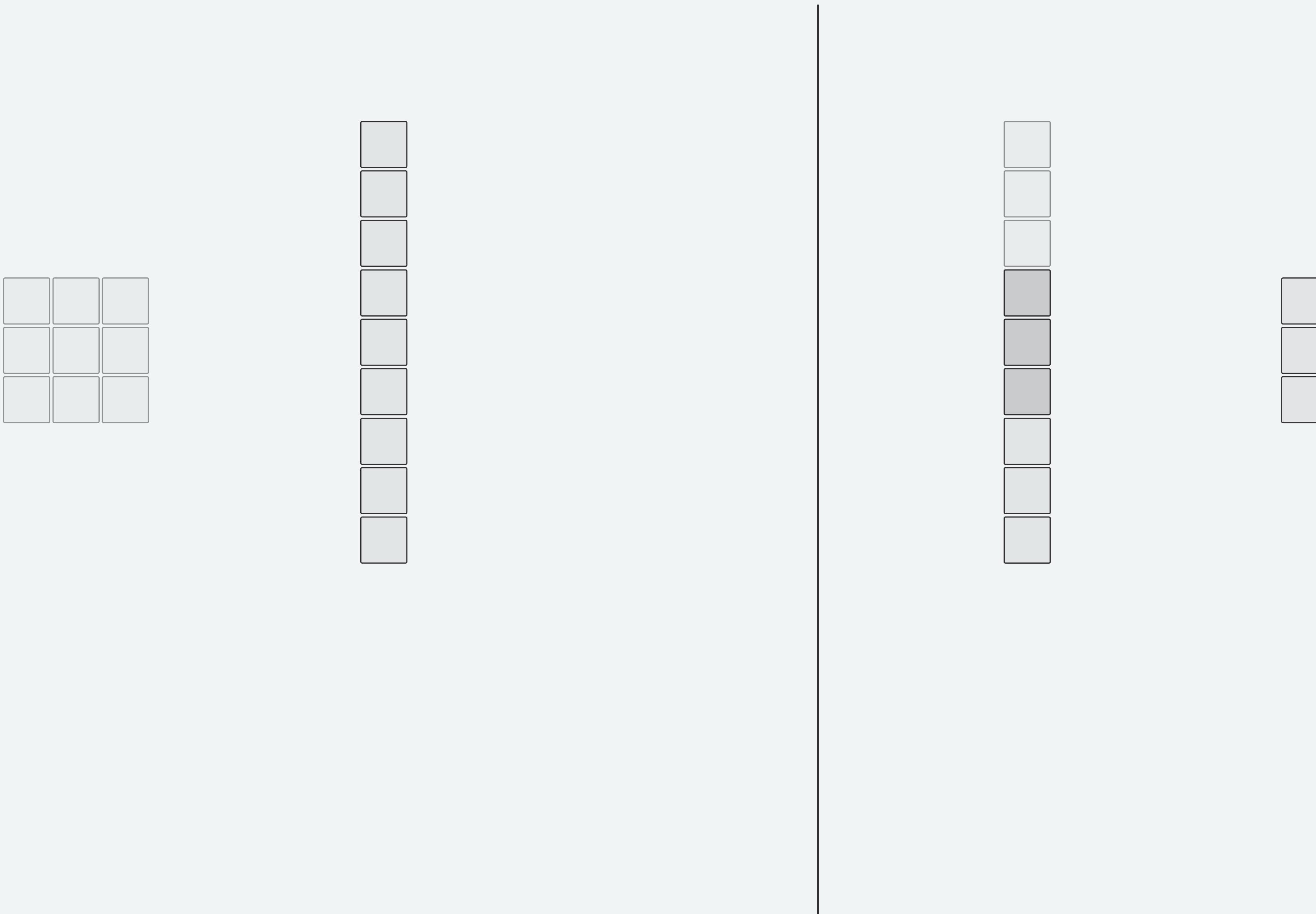
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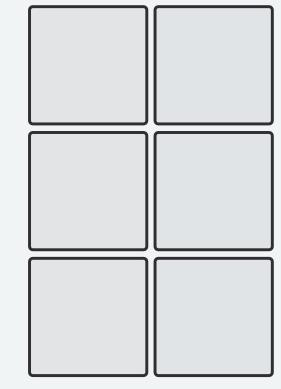
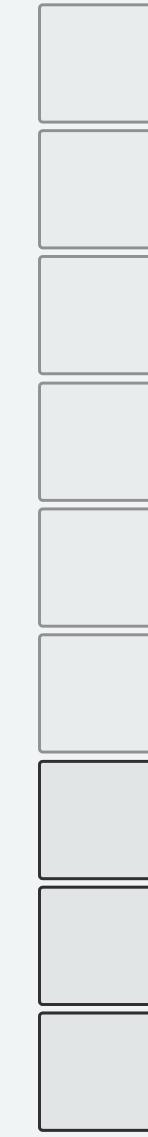
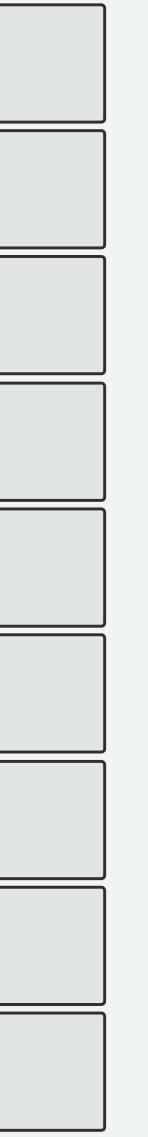
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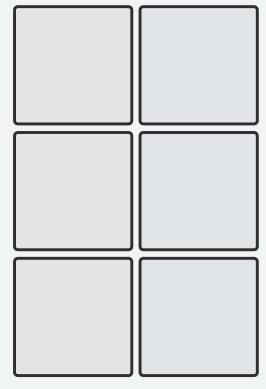
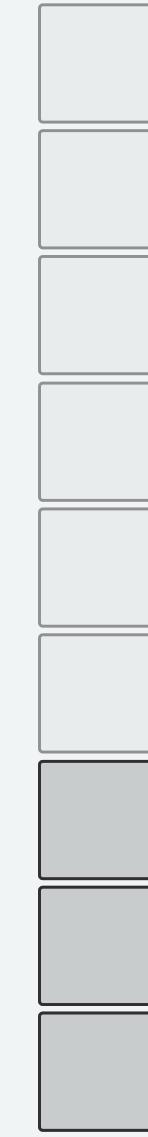
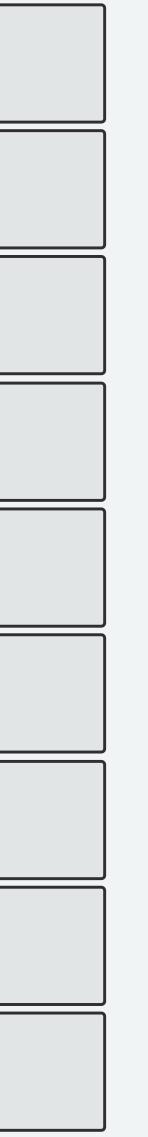
Vectorization



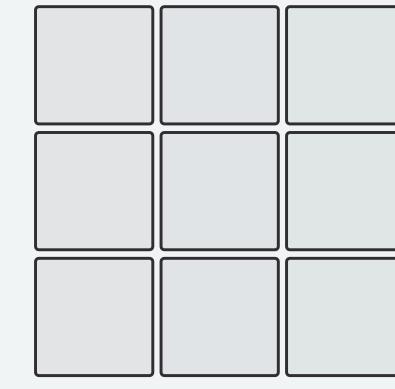
Vectorization



Vectorization



Vectorization



Final model

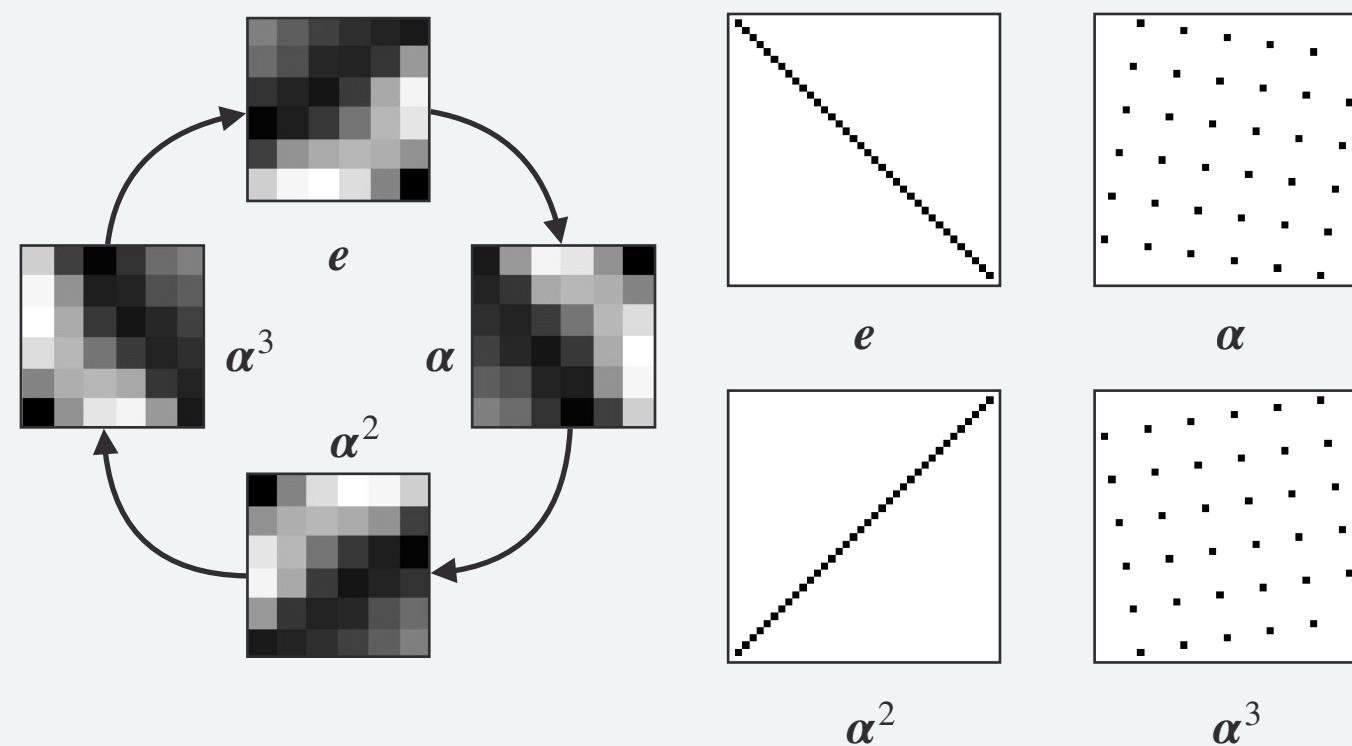
Filters

$$[\quad \phi_A(\square) \quad \dots \quad \phi_A^{n-1}(\square)]$$

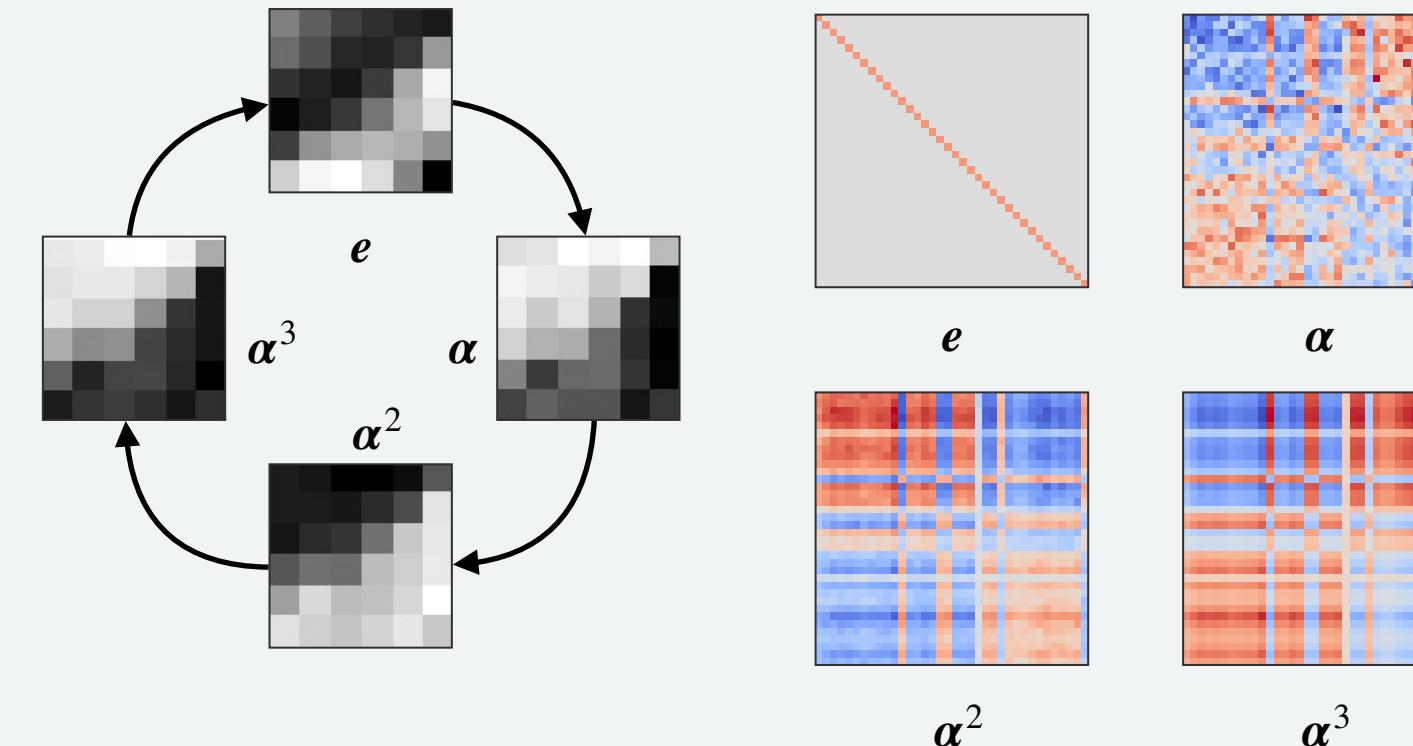
learn with backprop

$$\begin{aligned}\phi_A : \mathbb{R}^{n \times m} &\rightarrow \mathbb{R}^{n \times m} \\ X &\mapsto \text{vec}^{-1}(A \text{ vec}(X))\end{aligned}$$

Now we go from this...



... to this!



Invertibility loss

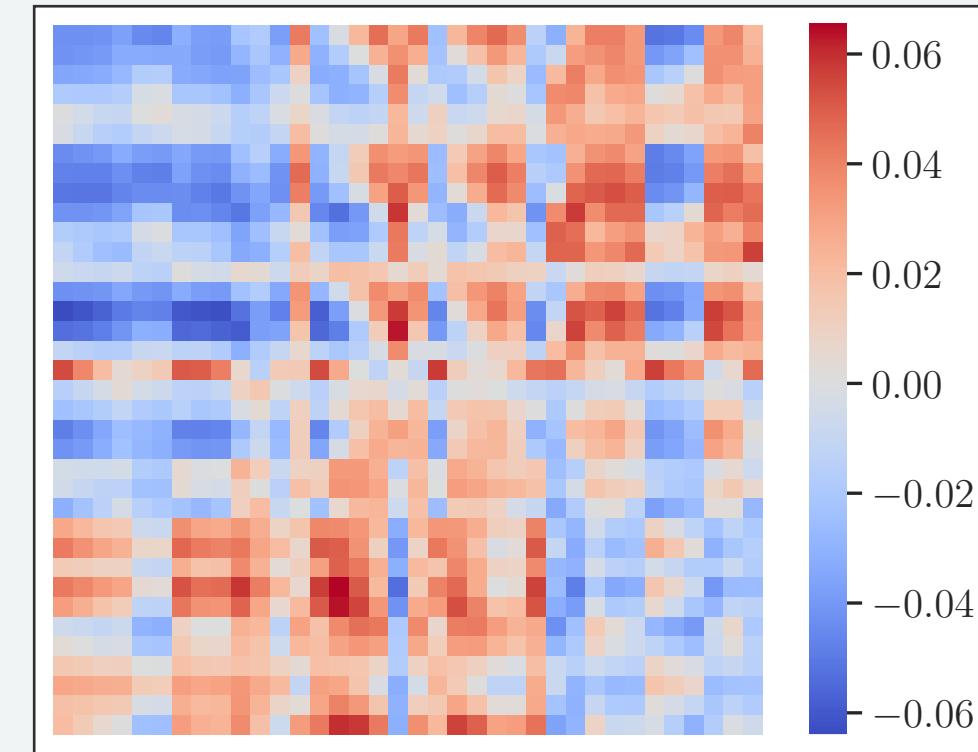
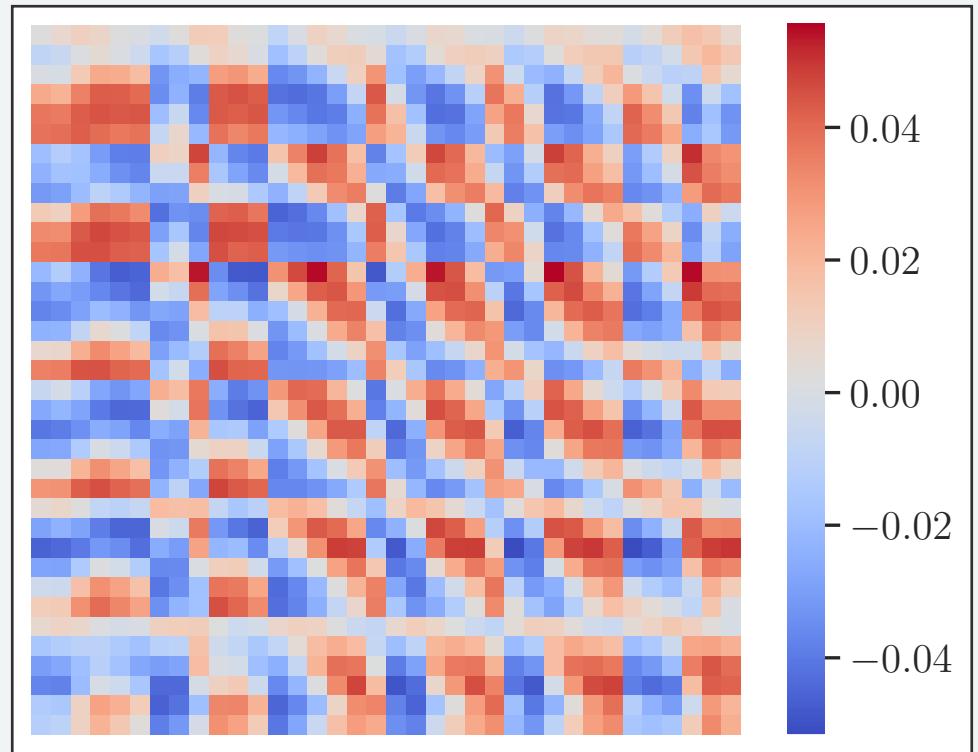
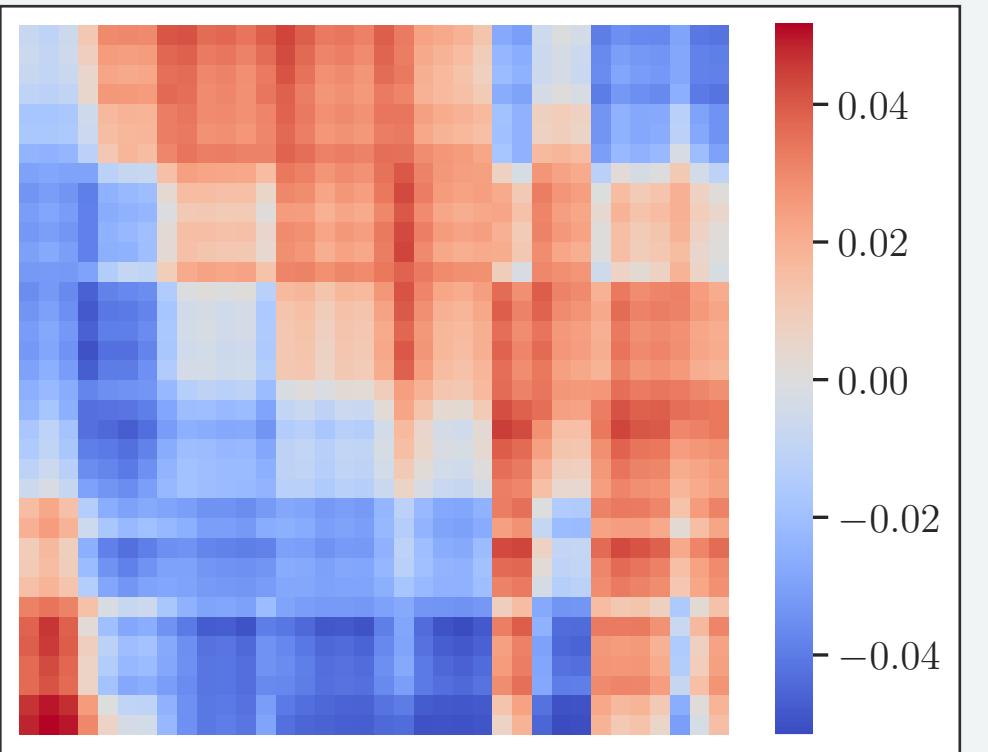
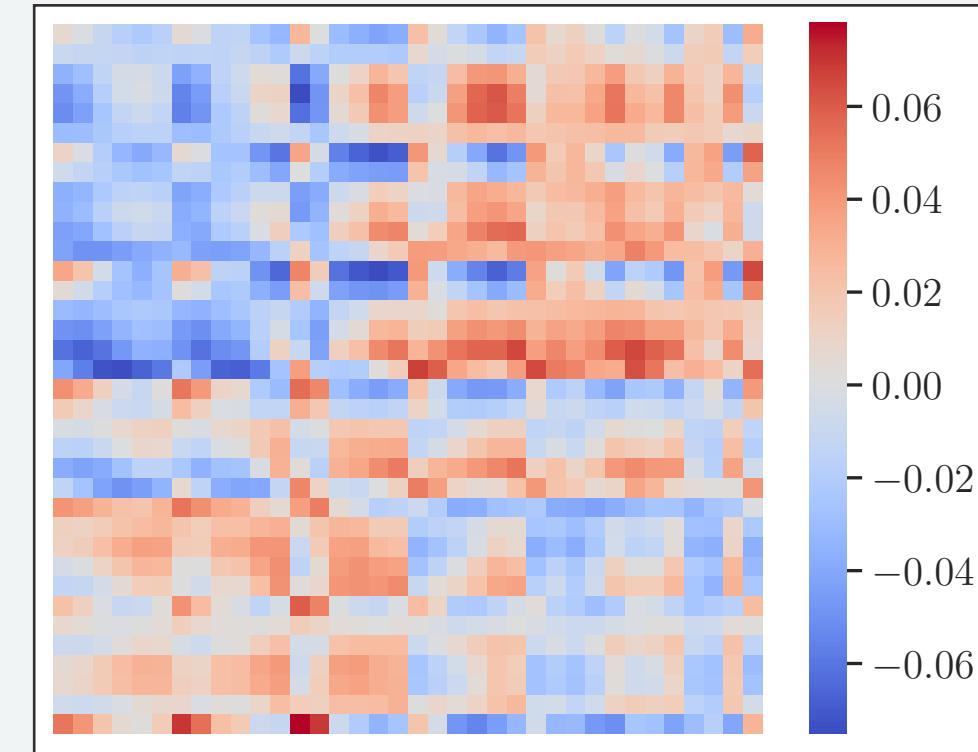
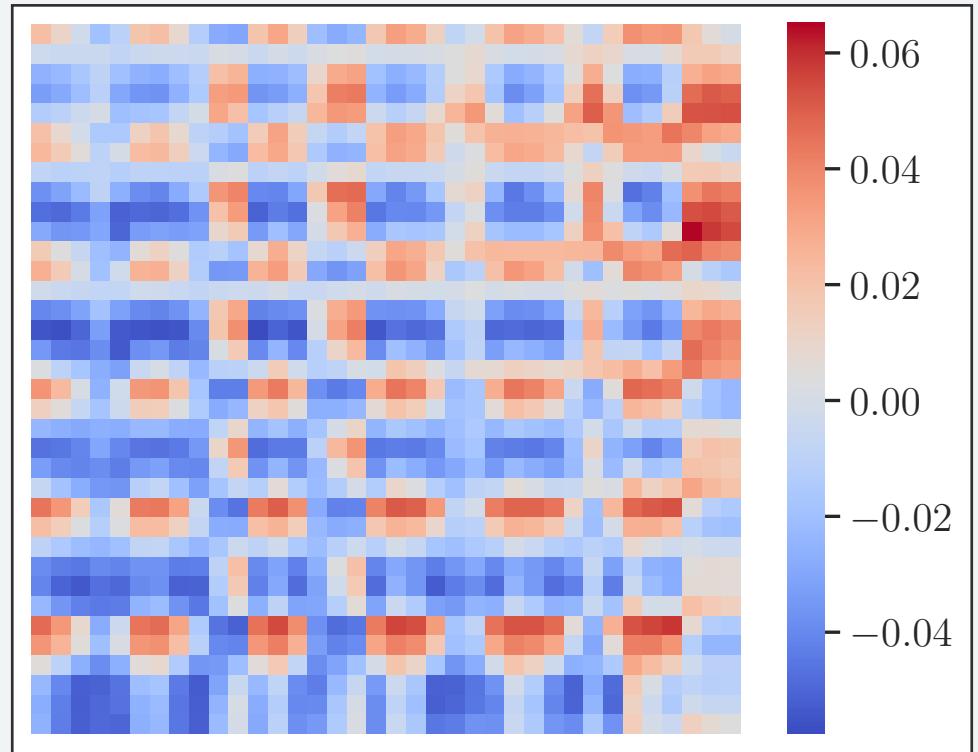
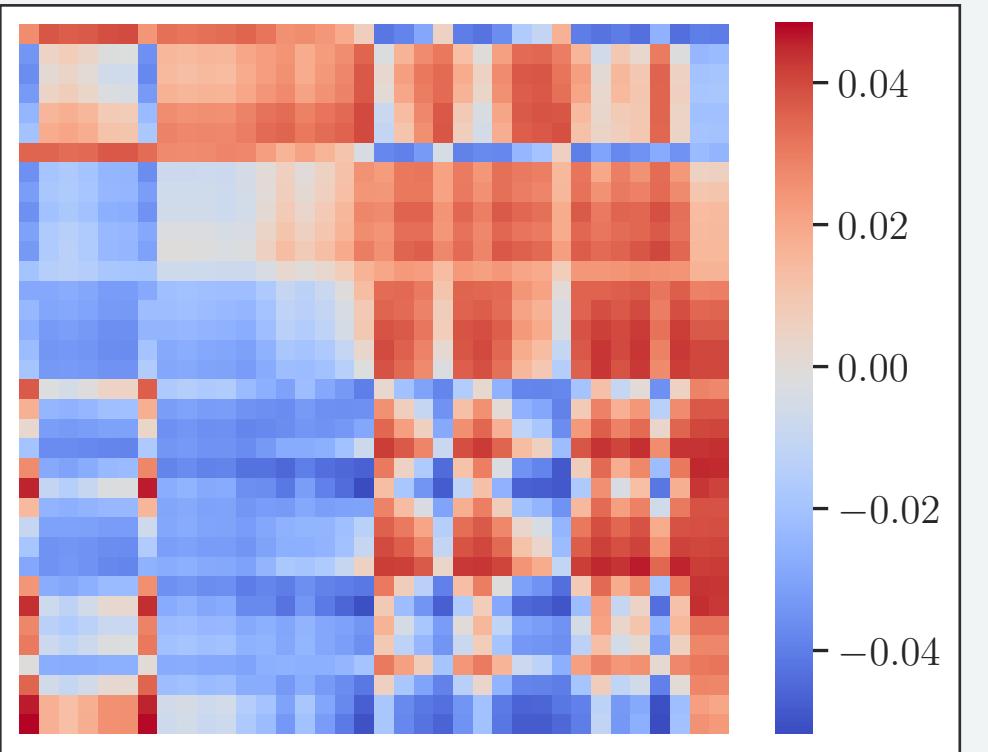
A needs to be invertible

$$L = \mu \|A\tilde{A} - I\|_F$$



Experiments

Group structures



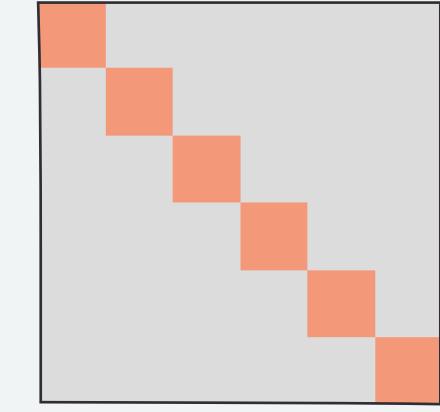
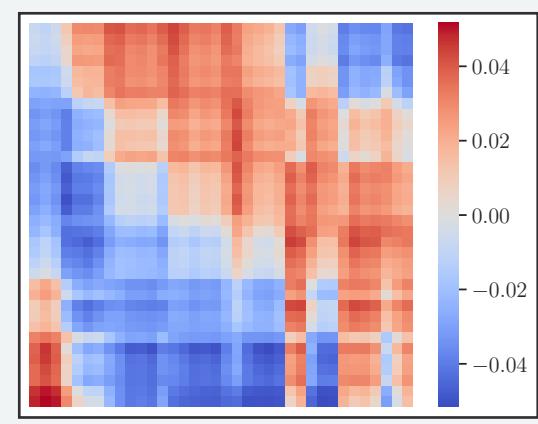
Skew-symmetric

Toeplitz

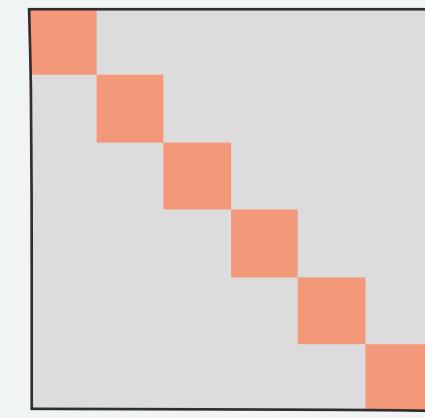
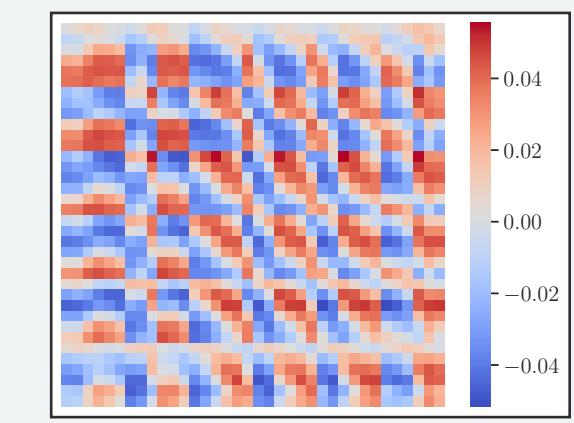
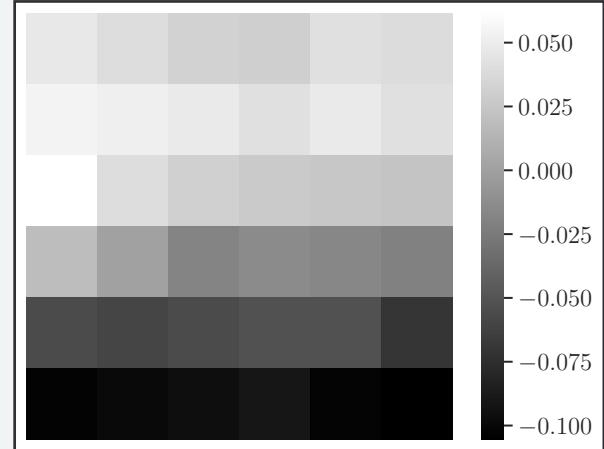
Multi-scale



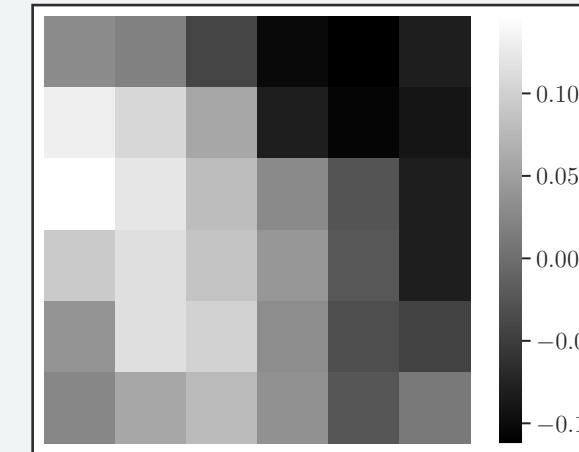
Interpreting the structures



=



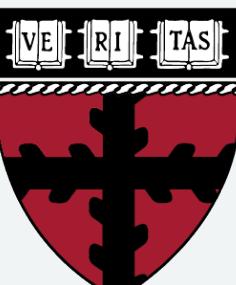
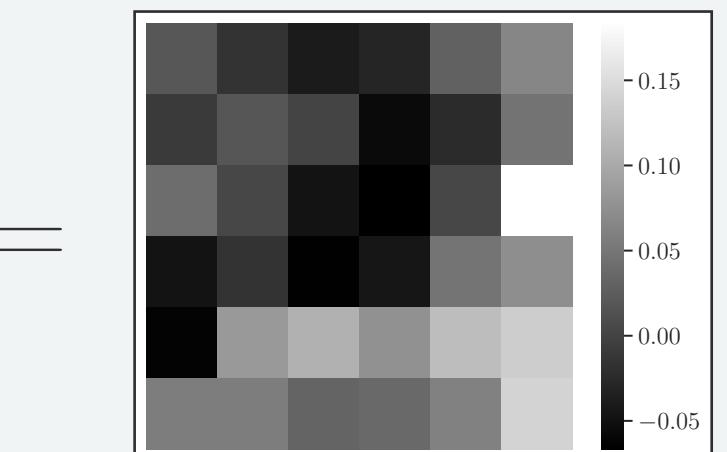
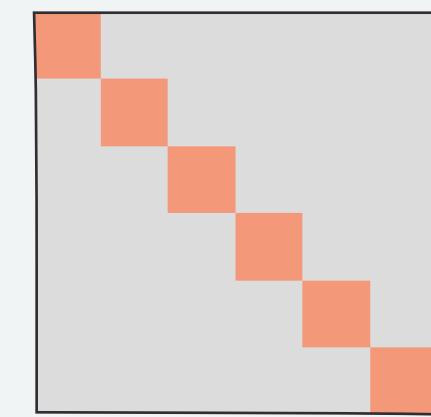
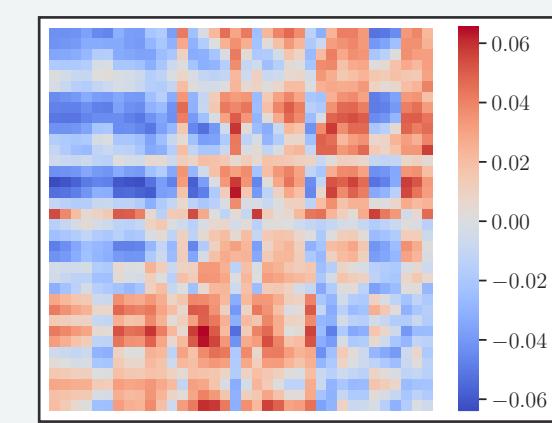
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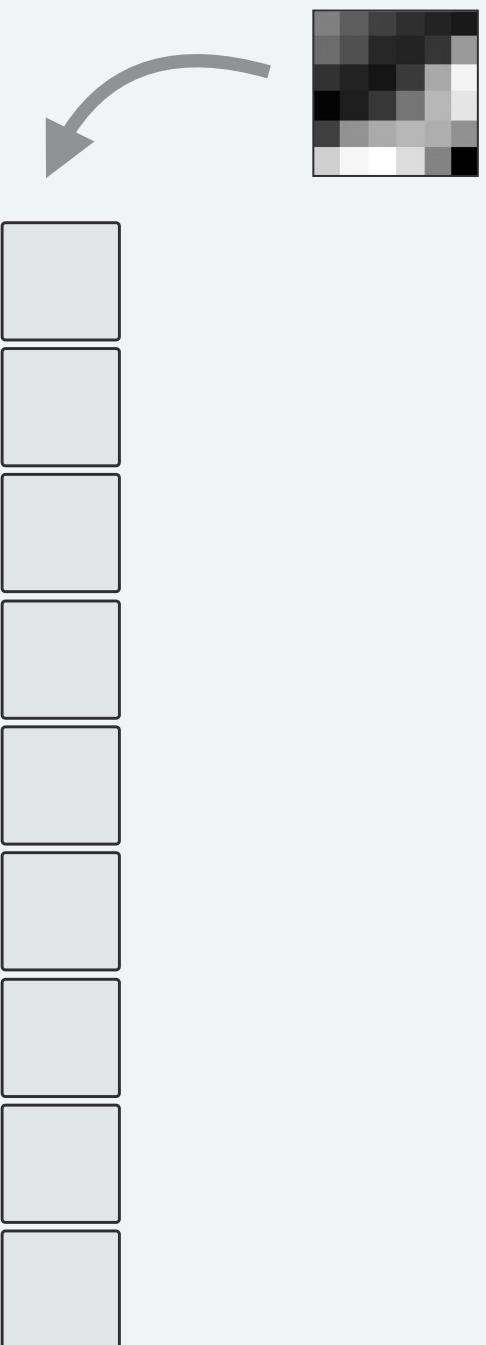
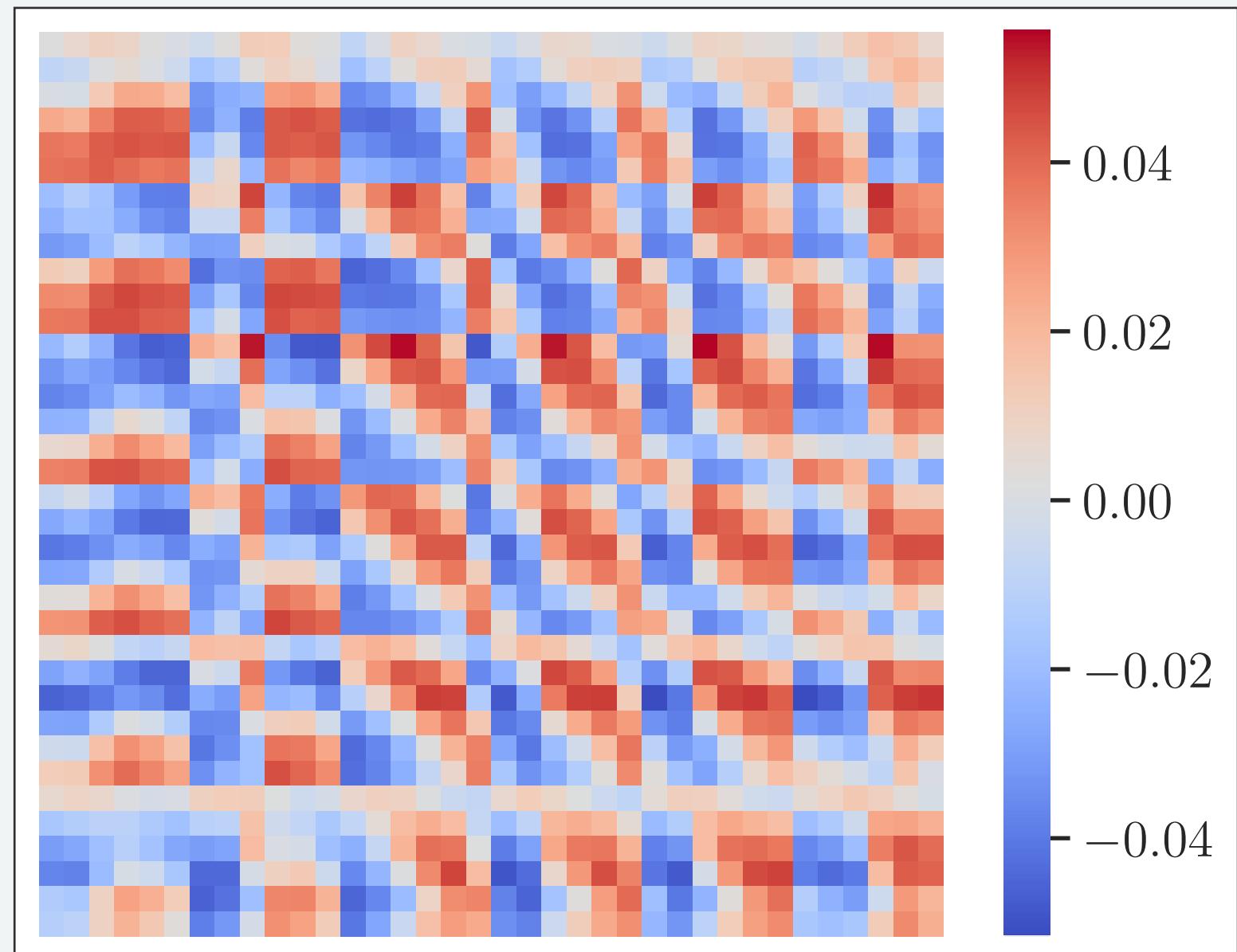
Skew-symmetric

Toeplitz

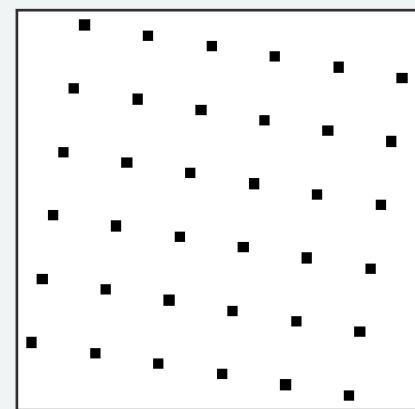
Multi-scale



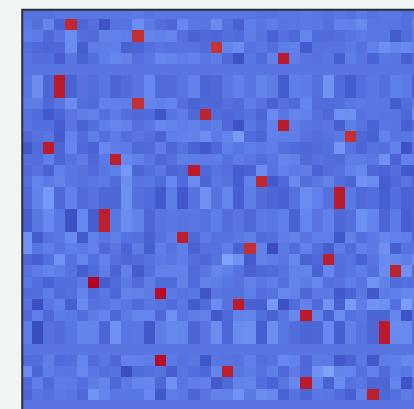
Interpreting the structures



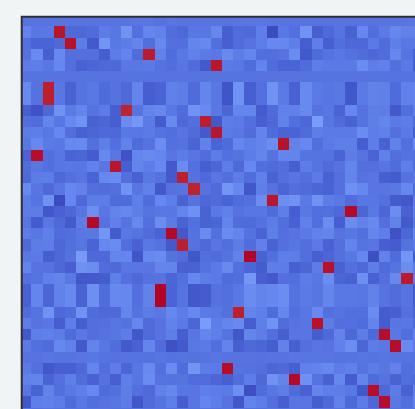
Rotations



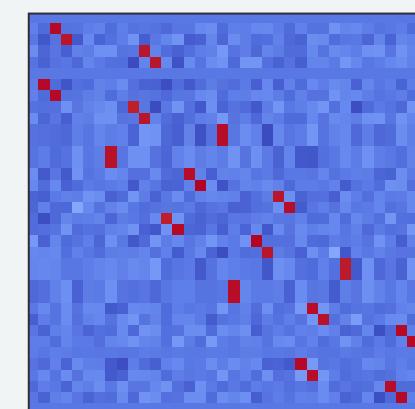
$\theta = 90^\circ$



$\theta = 60^\circ$

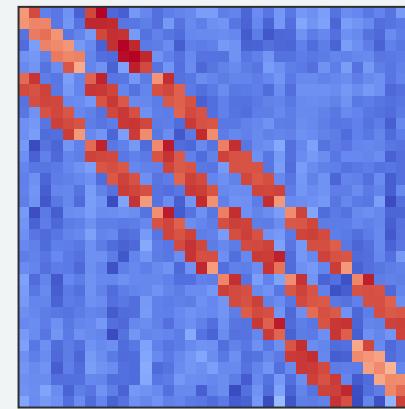


$\theta = 45^\circ$

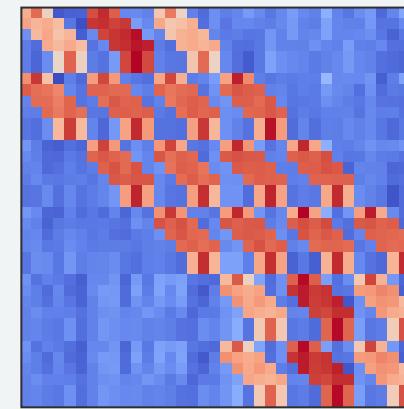


$\theta = 30^\circ$

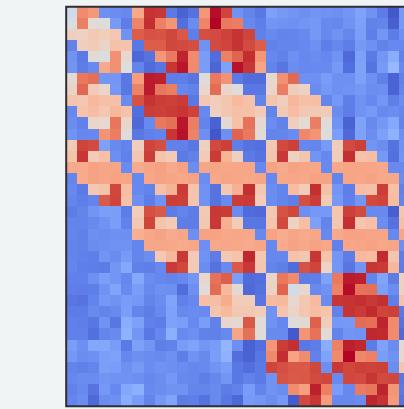
Pooling



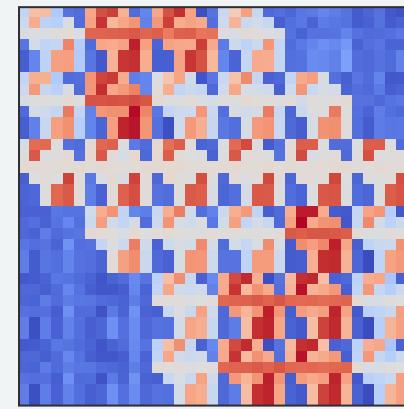
$r = 3$



$r = 4$

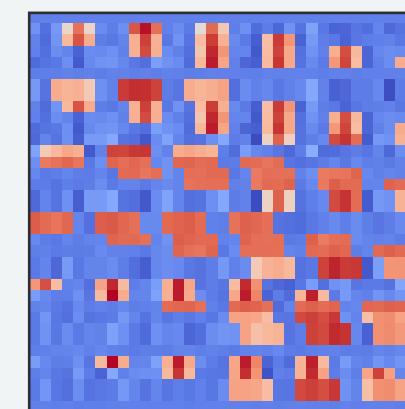


$r = 5$



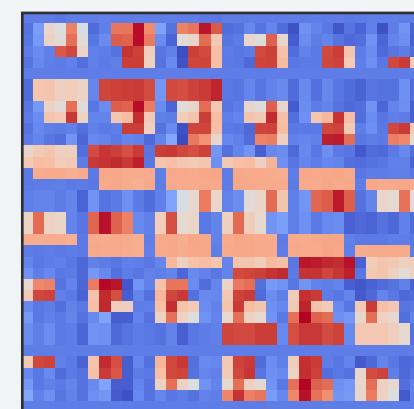
$r = 6$

... both!

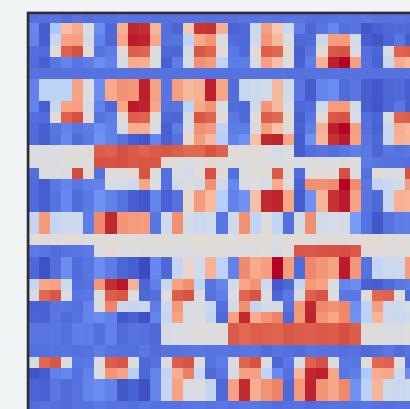


$\theta = 60^\circ$

$r = 4$



$r = 5$



$r = 6$

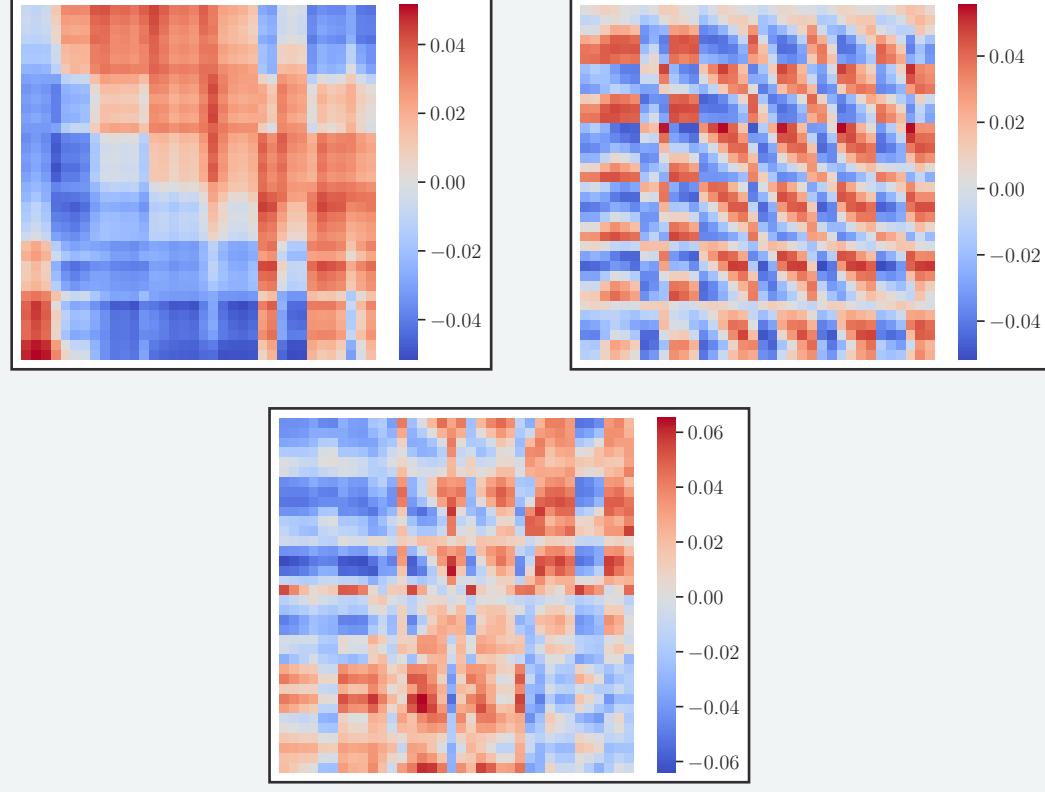
Observations

- aligned on grid
- acts on many pixels

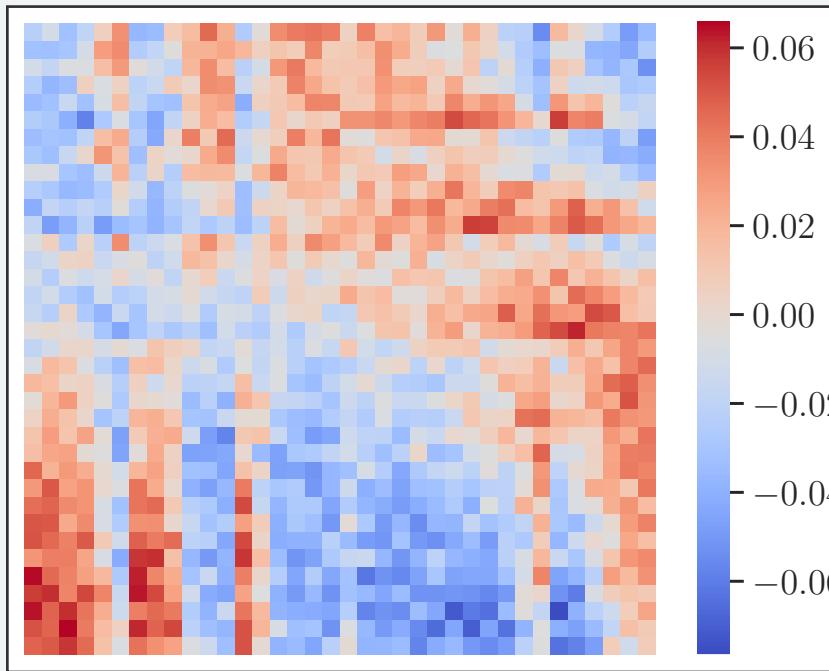


More experiments

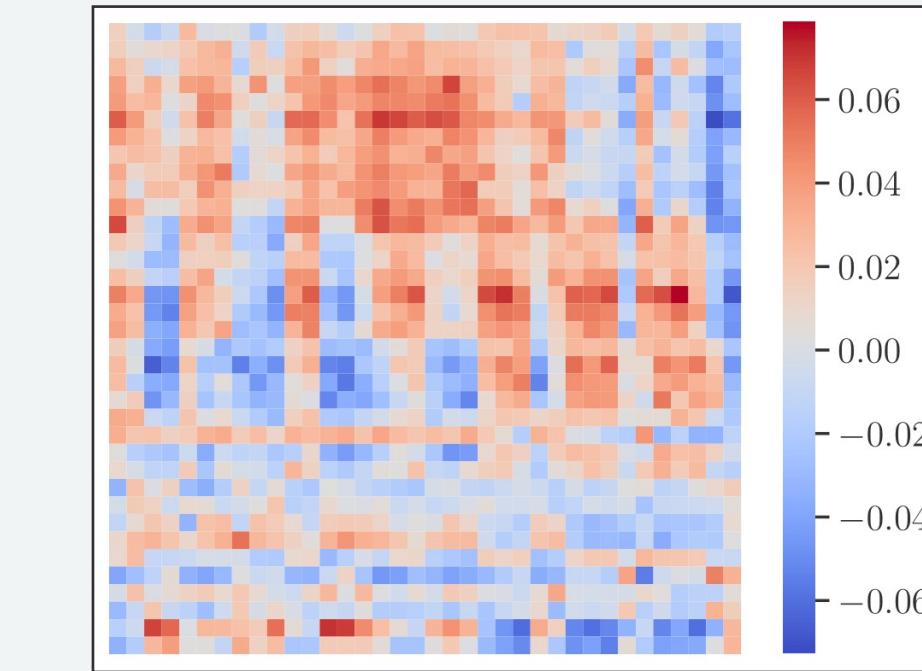
Actions are consistent



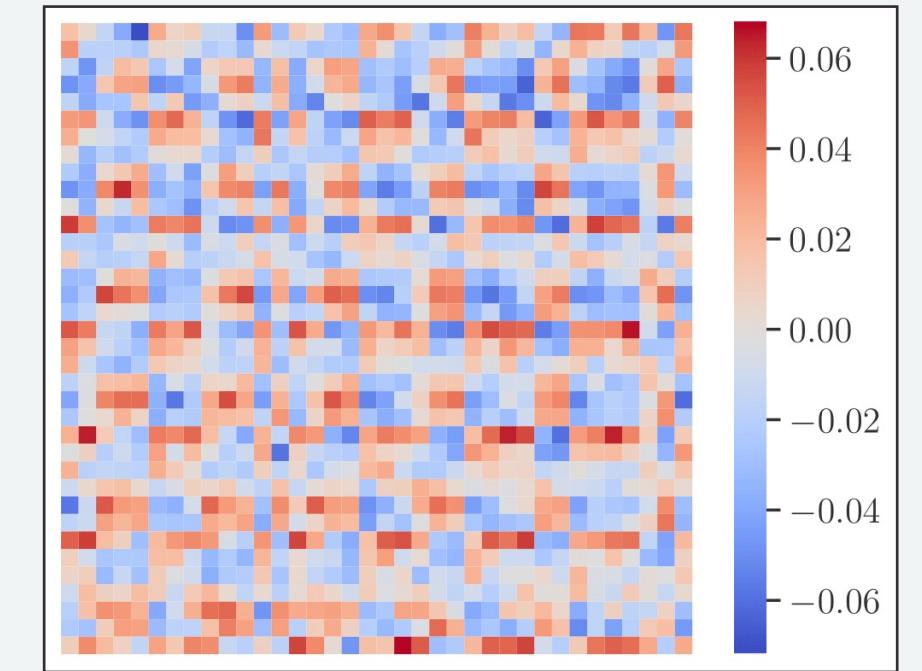
CIFAR10



MNIST

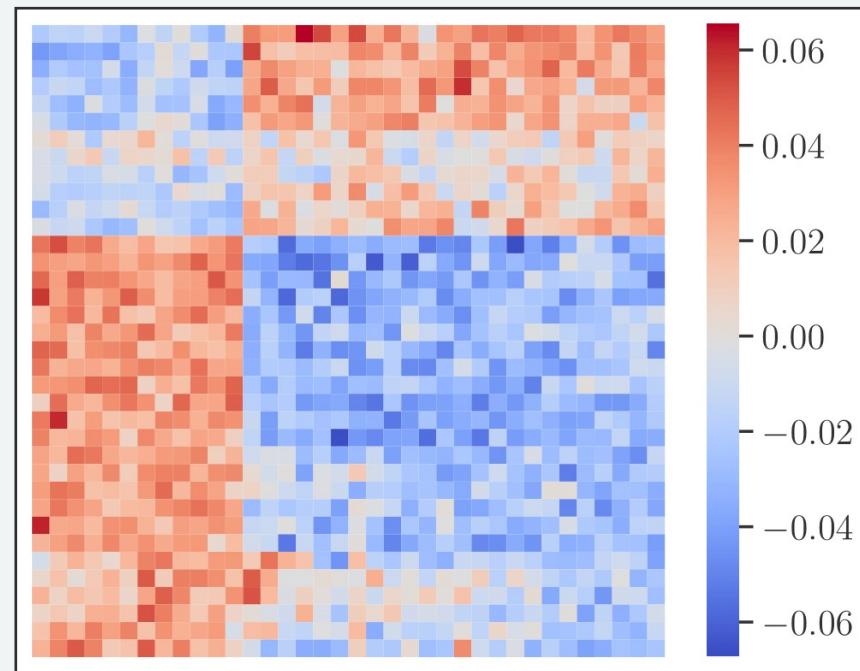


rotMNIST

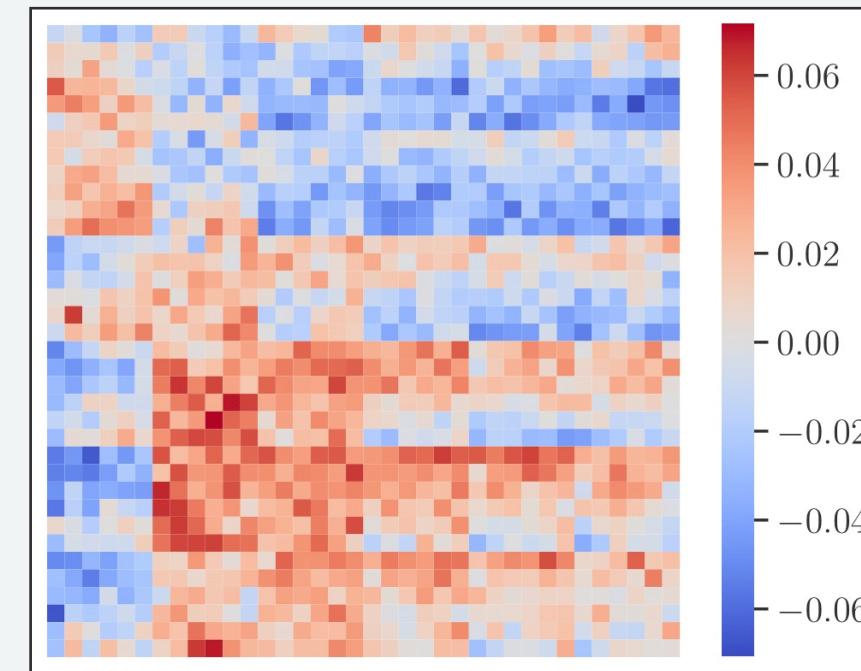


FashionMNIST

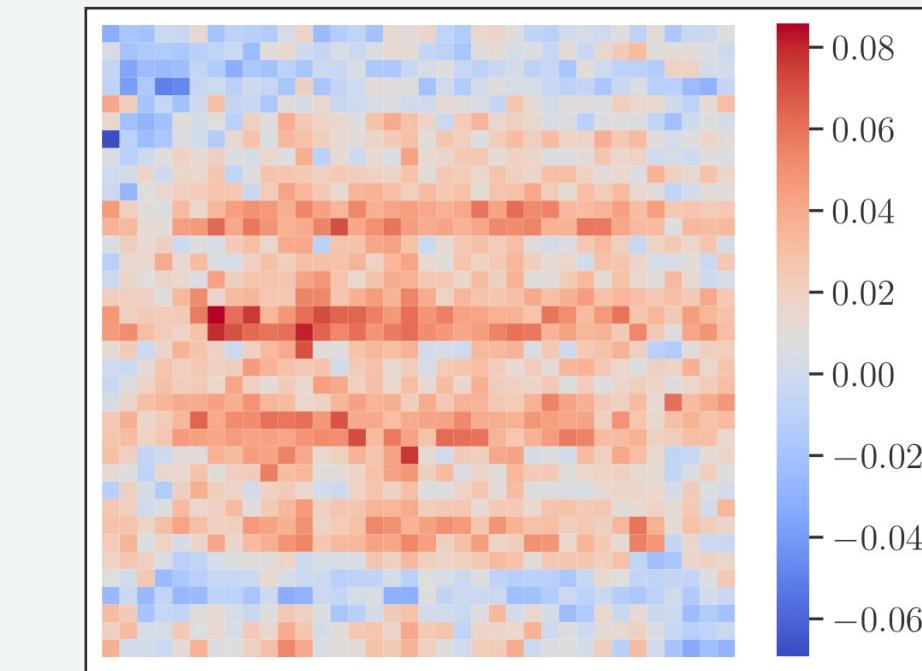
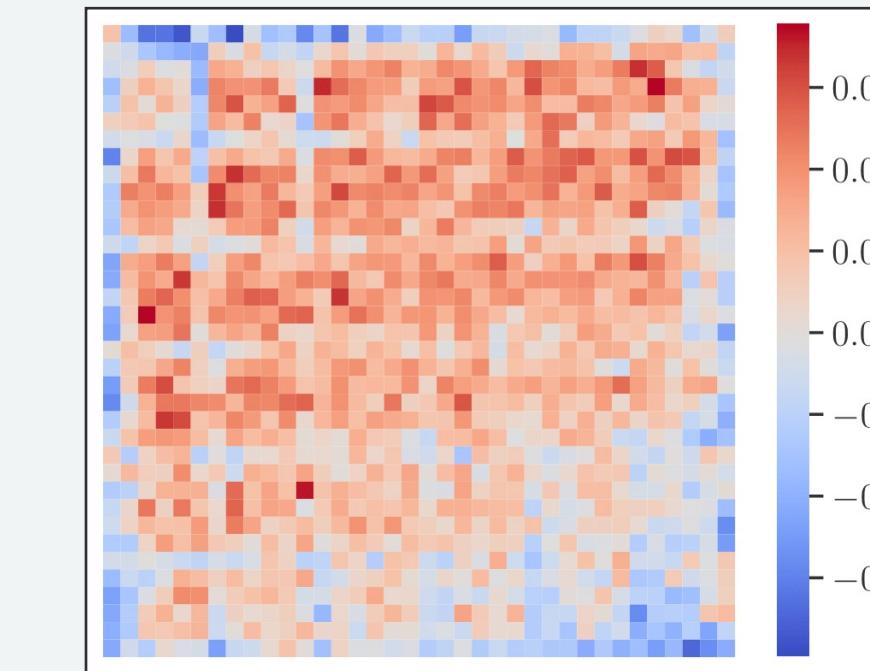
... and task dependent



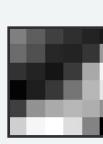
half (CIFAR10)



sim (MNIST)



Even more experiments

[ $\phi_A(\square)$... $\phi_A^{n-1}(\square)$] vs [] vs [  ... ]

Knowledge transfer

MNIST	LGN	P4CNN	Single channel	Same channels
Accuracy	98.86	98.68	98.52	97.42

Fashion MNIST	LGN	P4CNN	Single channel	Same channels
Accuracy	89.23	88.57	85.79	89.27

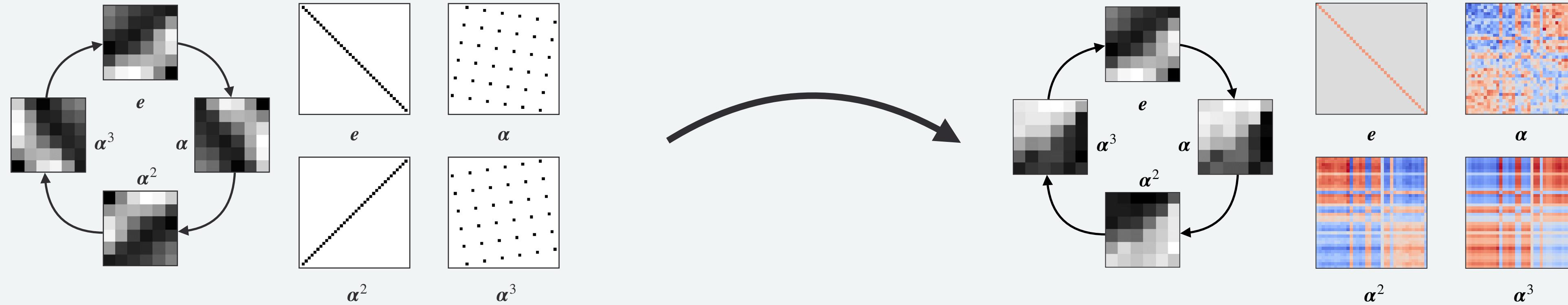
CNN comparison

	MNIST	rotMNIST	FashionMNIST	CIFAR10
LGCNN	99.27	93.75	91.46	79.03
P4CNN	99.35	92.96	91.44	75.26

(Based on ALL-CNN)

Concluding

Key takeaway



What the future holds

- non-cyclic groups
- apply to other domains
- systematic interpretation

THANK YOU

