

# A Wigner-Eckart theorem for group equivariant convolution kernels

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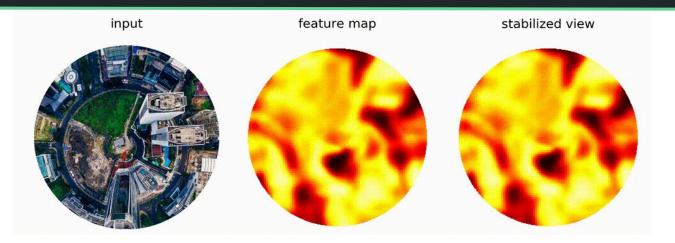
Maurice Weiler

AMLab, QUVA lab

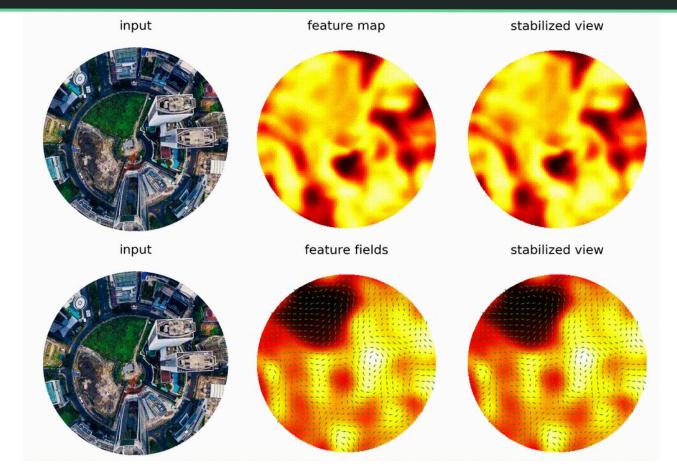
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# Rotation Equivariant Feature Maps

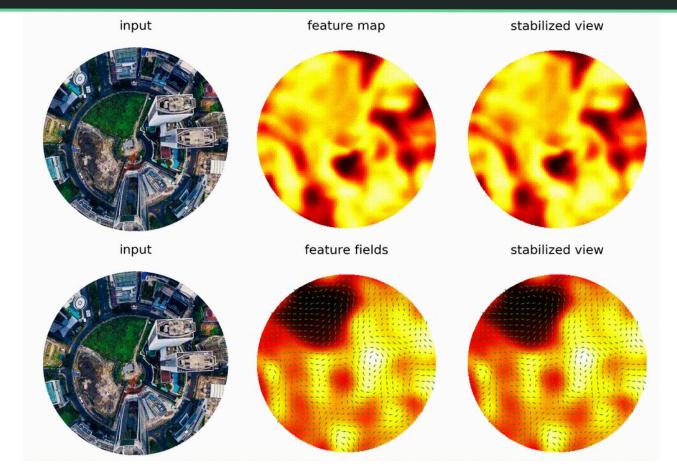


# Rotation Equivariant Feature Maps



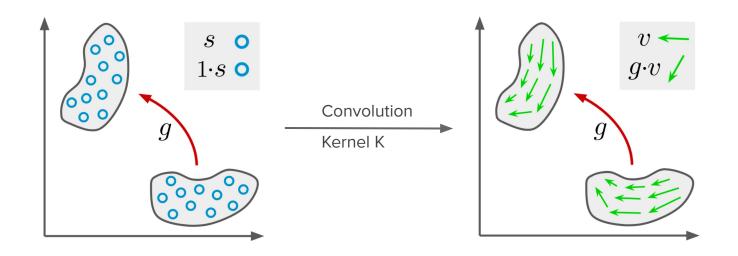
Visualisation by Gabriele Cesa

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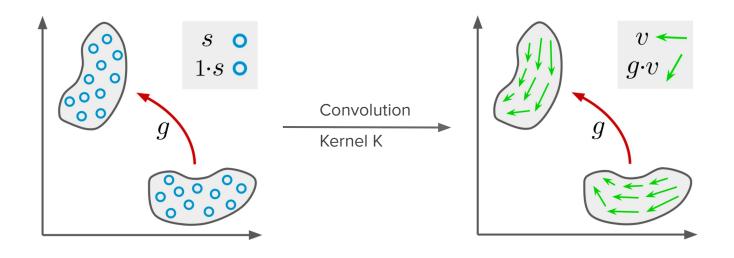


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# The G-Steerability Constraint



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$$K(gx) = \rho_{\text{out}}(g) \circ K(x) \circ \rho_{\text{in}}(g)^{-1}$$

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$$2j+1$$
 operators  $T_j^m, m=-j,\dots,j$  satisfying symmetry constraint  $\sum_{n=-j}^j D_j^{mn}(g)\,T_j^n=U(g)^\dagger T_j^m U(g)$   $\forall g\in {
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the matrix elements for fixed j, I, J are determined by single dof  $\lambda \in \mathbb{C}$  :  $\langle JM|T_j^m|ln \rangle = \lambda \cdot \langle JM|jm;ln \rangle$ 

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CG-coefficient, algebraically fixed

can we generalize this result to the matrix elements  $\langle JM|K(x)|ln\rangle$  of G-steerable kernels?

$$\langle JM \, | \, K(x) \, | \, ln \rangle \, = \, \sum_{j \in \widehat{G}} \sum_{i=1}^{m_j} \sum_{s=1}^{[J(jl)]} \sum_{m=1}^{[j]} \sum_{M'=1}^{[J]} \, \langle JM \, | \, c_{jis} \, | \, JM' \rangle \cdot \langle s, JM' \, | \, jm; ln \rangle \cdot \langle i, jm \, | \, x \rangle$$
 kernel matrix elements elements endomorphisms Clebsch-Gordan harmonics

**Wigner-Eckart for steerable kernels** = explain dof's in matrix elements of steerable kernels

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1. Peter-Weyl Theorem

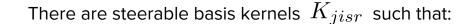
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- Peter-Weyl Theorem

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Wigner-Eckart for steerable kernels = explain dof's in matrix elements of steerable kernels

There are steerable basis kernels  $\,K_{iisr}\,$  such that:

$$K = \sum_{j \in \widehat{G}} \sum_{i=1}^{m_j} \sum_{s=1}^{[J(jl)]} \sum_{r=1}^{E_J} \lambda_{jisr} \cdot K_{jisr}$$

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Learnable Parameters

SO(2) with complex representations [1]

[1] Daniel E. Worrall et al. (2016). "Harmonic Networks: Deep Rotation and Translation

Equivariance" In: Conference on Computer Vision and Pattern Recognition (CVPR)

- SO(2) with complex representations [1]
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[3] Nathaniel Thomas et al. (2018). "Tensor Field Networks: Rotation- and Translation-Equivariant Neural Networks for 3D Point Clouds" In: arxiv e-Prints

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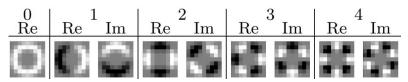
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- $\mathbb{Z}_2$  with real (regular) representations **[5]**

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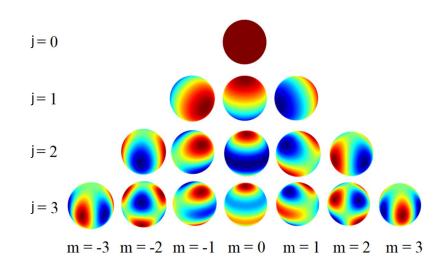
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#### Circular harmonics



#### Spherical harmonics





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