

Point Group Equivariant Convolutional Graph Neural Networks

Alex Heilman

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References

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Group Definition

A group G is a set of elements $\{g_1, \dots, g_n\}$ with a binary operation $*$: $G \times G \rightarrow G$ between elements that satisfies the conditions of identity, associativity, invertability, and closure.

Example: General Linear Group

The general linear group $GL(V)$ formed over some vector space V is the set of non-singular $d_v \times d_v$ matrices acting on V with the group operation being matrix multiplication. The general linear group is itself a vector space.

Vector Space Definition

A vector space V over a field K is a group of vectors equipped with a distributive scalar multiplication. Vectors are often defined by way of a basis set that spans the space under scalar multiplication.

Example: \mathbb{R}^3 , Real 3 Dimensional Space

Locations in physical space may be modeled with a three dimensional vector space \mathbb{R}^3 over the real numbers \mathbb{R} with basis functions $\hat{x}, \hat{y}, \hat{z}$.

Example: Functions on Real 3 Dimensional Space

Scalar functions on physical space also form a vector space over the real numbers, albeit infinite-dimensional. In this case, the group operation between vectors (functions) is point-wise addition.

We may construct new vector spaces from sets of existing vector spaces by taking tensor products and direct sums.

We may form direct sums $V \oplus W$ of vector spaces V, W by block-diagonal concatenation. This operation enjoys scalar distributivity to respective subspaces with the set of scalars $K_V \oplus K_W$.

Example: Direct Sum of Matrices

$$\begin{bmatrix} a_1 & b \\ c & a_2 \end{bmatrix} \oplus \begin{bmatrix} d_1 & 0 \\ 0 & d_2 \end{bmatrix} = \begin{bmatrix} a_1 & b & 0 & 0 \\ c & a_2 & 0 & 0 \\ 0 & 0 & d_1 & 0 \\ 0 & 0 & 0 & d_2 \end{bmatrix}$$

Direct sums of vector spaces are themselves vector spaces.

Tensor Products

Tensor products $V \otimes W$ of vector spaces V, W are uniquely bilinear so that $\lambda V \otimes W = V \otimes \lambda W = \lambda(V \otimes W)$.

Example: Tensor Product of Matrices

Also known as "Kronecker Product".

$$\begin{bmatrix} a_1 & b \\ c & a_2 \end{bmatrix} \otimes \begin{bmatrix} d_1 & 0 \\ 0 & d_2 \end{bmatrix} = \begin{bmatrix} a_1 d_1 & 0 & b d_1 & 0 \\ 0 & a_1 d_2 & 0 & b d_2 \\ c d_1 & 0 & a_2 d_1 & 0 \\ 0 & c d_2 & 0 & a_2 d_2 \end{bmatrix}$$

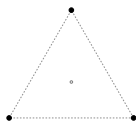
Tensor products of vector spaces are themselves vector spaces.

Group Representations

A representation ρ_G of a group G is a homomorphism from elements g to a set of linear operators (square matrices).

Example: 3D Representation of C_3

Consider three identical points in 3D space forming an equilateral triangle.



These clearly are symmetrical under three-fold rotations about the origin in the xy plane. These C_3 group actions act on this Cartesian basis with the representation ρ defined:

$$\rho(\mathbb{I}) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad \rho(C_3) = \begin{bmatrix} -\frac{1}{2} & -\frac{\sqrt{3}}{2} & 0 \\ \frac{\sqrt{3}}{2} & -\frac{1}{2} & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad \rho(C_3^2) = \begin{bmatrix} -\frac{1}{2} & \frac{\sqrt{3}}{2} & 0 \\ -\frac{\sqrt{3}}{2} & -\frac{1}{2} & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Irreducible Representations (IRs)

For atomic arrangements, 3D group representations ρ are often reducible in terms of a direct sum of 'smaller' group representations $\rho^{(\alpha)}$:

$$\rho = \bigoplus_{\alpha} c_{\alpha} \rho^{(\alpha)}$$

Maschke's theorem guarantees that any given representation is always decomposable as a direct sum of irreducible representations.

This set may always be taken to satisfy:

- Unitarity
- Orthogonality
- $\sum_{\alpha} d_{\alpha}^2 = N$ where d_{α} is the dimension of IR α and N is the order

Example: IRs of D_3 The previously shown representation of C_3 elements is reducible into a two-dimensional subspace and a one-dimensional subspace of D_3 .

$$\rho(\mathbb{I}) = \rho^{(2)}(\mathbb{I}) \oplus \rho^{(1)}(\mathbb{I}) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \oplus [1]$$

$$\rho(C_3) = \rho^{(2)}(C_3) \oplus \rho^{(1)}(C_3) = \begin{bmatrix} -\frac{1}{2} & -\frac{\sqrt{3}}{2} \\ \frac{\sqrt{3}}{2} & -\frac{1}{2} \end{bmatrix} \oplus [1]$$

$$\rho(C_3^2) = \rho^{(2)}(C_3^2) \oplus \rho^{(1)}(C_3^2) = \begin{bmatrix} -\frac{1}{2} & \frac{\sqrt{3}}{2} \\ -\frac{\sqrt{3}}{2} & -\frac{1}{2} \end{bmatrix} \oplus [1]$$

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Orthogonality Theorems

IRs are orthogonal in the following ways:

$$\frac{1}{N} \sum_g \chi^{(\alpha)*}(g) \chi^{(\beta)}(g) = \delta_{\alpha\beta}$$

$$\sum_{\alpha} \chi^{(\alpha)*}(c_k) \chi^{(\alpha)}(c_h) = \frac{N}{N_k} \delta_{kh}$$

where N is the number of elements in G and N_k is the number of elements in equivalence class k .

This allows us to decompose reducible representations by determining the coefficients of expansion c_{α} as:

$$c_{\alpha} = \frac{1}{N} \sum_g \chi^{(\alpha)*}(g) \chi(g)$$

Example: d-shell Splitting in Octohedral Coordinations

The octohedral complex's symmetry group is O , with it's character table and the $\Gamma^{\ell=2}$ representation:

O	$1\langle \mathbb{I} \rangle$	$8\langle C_3 \rangle$	$3\langle C_2 \rangle$	$6\langle C'_2 \rangle$	$6\langle C_4^3 \rangle$
$(d) \Gamma^{\ell=2}$	5	-1	1	1	-1
A_1	1	1	1	1	1
A_2	1	1	1	-1	-1
E	2	-1	2	0	0
T_1	3	0	-1	-1	1
T_2	3	0	-1	1	-1

Orthogonality then gives $\gamma^{\ell=2} = E \oplus T_2$. In practice, this results in a 5-fold degeneracy being lifted into a two- and three-fold degeneracy.

Basis Functions (cont.)

Example: 3D Basis Functions of D_3

Consider previous 3D representation of C_3 rotations in D_3 , which act on vectors \vec{r}_ρ :

$$\vec{r}_\rho = \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \vec{r}_{\rho^{(2)}} \oplus \vec{r}_{\rho^{(1)}} = \begin{bmatrix} x \\ y \end{bmatrix} \oplus [z]$$

Clearly, x, y is a basis transforming as Γ^2 and z is a basis for Γ^1 .

Example: Tight Binding

The tight binding approximation often uses localized Hydrogen-like orbitals ψ_{nm}^ℓ as a basis for many-body systems

Coupling Coefficients

Consider a direct product decomposition of some irreps Γ :

$$\Gamma^\alpha \otimes \Gamma^\beta = \bigoplus_{\gamma} c_{\alpha\beta\gamma} \Gamma^\gamma$$

Products of basis functions $u_i^\alpha v_j^\beta$ then decompose similarly into a direct sum of irreps with basis functions ψ_n^γ via the coupling coefficients $U_{\alpha i \beta j}^\gamma$ as:

$$\psi_n^\gamma = \sum_{i,j} U_{\alpha i \beta j}^\gamma u_i^\alpha v_j^\beta$$

Example: Clebsch-Gordan Coefficients

The Clebsch-Gordan coefficients $C_{\ell_1 m_1 \ell_2 m_2}^{\ell_f m_f}$ are the coupling coefficients of $SO(3)$, which relate tensor product spaces of spherical harmonics Y_m^ℓ to direct sums of spherical harmonics.

$$Y_{\ell_1}^{m_1}(\Omega) Y_{\ell_2}^{m_2}(\Omega) = \sum_{\ell_3, m_3} \sqrt{\frac{(2\ell_1 + 1)(2\ell_2 + 1)}{4\pi(2\ell_3 + 1)}} C_{\ell_1 m_1 \ell_2 m_2}^{\ell_3 m_3} C_{\ell_1 0 \ell_2 0}^{\ell_3 0} Y_{\ell_3}^{m_3}(\Omega)$$

Diri's Formula [diri1979]:

$$(U_{\alpha i \beta j}^n)^m = \sqrt{\frac{d_\gamma}{N_G}} \left[\sum_{g \in G} \Gamma_{qq}^\alpha(g) \Gamma_{ss}^\beta(g) \Gamma_{aa}^{\gamma\dagger}(g) \right]^{-\frac{1}{2}} \cdot \sum_{g \in G} \Gamma_{iq}^\alpha(g) \Gamma_{js}^\beta(g) \Gamma_{na}^{\gamma\dagger}(g)$$

An equivariant function $f : X \rightarrow Y$, where X, Y are vector spaces, is one that 'commutes' with a group's actions, satisfying:

$$f\left(\mathcal{D}^X(g)x\right) = \mathcal{D}^Y(g)f(x)$$

Tensor products are uniquely equivariant with respect to their argument vector spaces.

Physics assumes there exists a map between configurations and properties of physical systems:

$$\{\vec{r}_i\} \xrightarrow{\text{Nature}} \{\vec{r}'_i\}$$

Neural network techniques assume maps between abstract input and output spaces exist:

$$X \xrightarrow{\text{Neural Network}} Y$$

and that these may be expressed in a basis of adequately large neural networks.

Why Equivariant Functions? (cont.)

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Group Equivariant Networks

Physical processes respect coordinate system rotations R :

$$\{R\vec{r}_i\} \xrightarrow{\text{Nature}} \{R\vec{r}'_i\}$$

In general, neural networks do not:

$$RX \xrightarrow{\text{Neural Network}} ?$$

So what do we want?

We want equivariant networks for physics!

$$RX \xrightarrow[\text{Neural Network}]{\text{Equivariant}} RY$$

In equivariant networks, we consider feature vectors in basis of representation space as:

V_j^α

with indexes α denoting the irrep it transforms as, and i denoting the dimension of irrep space α .

Most modern equivariant networks are specifically $SO(3)$ -Equivariant.

- ▶ Infinite order \rightarrow infinite irreps
- ▶ Irreps are Wigner \mathcal{D}^ℓ matrices
- ▶ Natural basis set Y_m^ℓ of dimension $d_\ell = 2\ell + 1$

Many models are further referred to as $E(3)$ -equivariant for the Euclidean group (add parity and translation invariance).

Tensor field networks [2] use $SO(3)$ equivariant convolution:

$$(v_{nc}^{L+1})_m^{\ell} = (v_{nc}^L)_m^{\ell} + \sum_{b \in \mathcal{N}(n)} \sum_{\ell_f m_f, \ell_i m_i}^{\ell_{\max} m_{\max}} c_{\ell_f m_f \ell_i m_i}^{\ell m} (F_c^L(r_{nb}))_{m_f}^{\ell_f} (v_{bc}^L)_{m_i}^{\ell_i}$$

- ▶ v_{nc}^L : Node feature of node n , channel c , layer L
- ▶ $c_{\ell_f m_f \ell_i m_i}^{\ell_o m_o}$: Clebsch-Gordan coefficients
- ▶ F_c^L : Filter function (trainable)
- ▶ r_{nb} : Radius between nodes n and neighbor $b \in \mathcal{N}(n)$

F is generally a neural network; r is often expanded with some radial basis function (RBF): Gaussian, Bessel, etc.

Index vectors by α, i from site-symmetry group instead!

$$(v_{nc}^{L+1})_m^\ell = (v_{nc}^L)_n^\gamma + \sum_{b \in \mathcal{N}(n)} \sum_{\alpha i, \beta j} U_{\alpha i \beta j}^{\gamma n} (F_c^L(r_{nb}))_j^\beta (v_{bc}^L)_i^\alpha$$

- ▶ Natural cutoff (finite summation over α, β)
- ▶ Natural readout for symmetric properties ($\gamma = 1$)
- ▶ Accounts for all physical symmetry but not more

Space Groups

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Alex Heilman

Semidirect product of point group R and lattice translation group T :

$$G = T \rtimes R$$

- ▶ Describes all symmetries of crystals
- ▶ Infinite order \rightarrow infinite irreps
- ▶ Can learn features associated with point group and induce for space group

Point Groups and Space Groups

Induced Representations

"Opposite of a reduced representation"

Use subgroup G representation $\tilde{\rho}$ to form representation ρ of parent H :

$$\rho_{\alpha i, \beta j}(h) = \begin{cases} \tilde{\rho}(g)_{ij} & \text{if } h_{\alpha}^{-1} h h_{\beta} = g \in G \\ 0 & \text{else} \end{cases}$$

where α indexes a coset decomposition of H into $G \subset H$.

Example: Induced Representation of S_2

Take trivial group E with representation $\tilde{\rho}(E) = 1$. Induced rep. of S_2 then is:

$$\rho_{S_2}(\mathbb{I}) = \begin{bmatrix} \tilde{\rho}(\mathbb{I}) & \tilde{\rho}([12]) \\ \tilde{\rho}([12]) & \tilde{\rho}([12][12]) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$\rho_{S_2}([12]) = \begin{bmatrix} \tilde{\rho}([12]) & \tilde{\rho}([12][12]) \\ \tilde{\rho}([12][12]) & \tilde{\rho}([12][12][12]) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$$

Alex Heilman

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- Take hydrogen-like orbitals and treat them as $SO(3)$ features
- Allows for the learning of all rotational symmetries but doesn't enforce them from physical considerations.
- Predicts DFT Hamiltonian from first large set of data

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- [2] Nathaniel Thomas et al. "Tensor field networks: Rotation- and translation-equivariant neural networks for 3D point clouds". In: *arXiv preprint arXiv:1802.08219* (2018). arXiv: 1802.08219 [cs.LG]. URL: <https://arxiv.org/abs/1802.08219>.