

Point Group Equivariant Convolutional Graph Neural Networks

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June 4, 2025

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Overview

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- ▶ Brief review of mathematics
- ▶ Group representation theory
 - ▶ Irreps
 - ▶ Basis Functions
 - ▶ Coupling Coefficients
- ▶ Equivariant networks
 - ▶ $SO(3)$ Equivariance
- ▶ Applications

Group Definition

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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.

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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.

Direct Sums

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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

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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".

$$\begin{bmatrix} a_1 & b \\ c & a_2 \end{bmatrix} \otimes \begin{bmatrix} d_1 & 0 \\ 0 & d_2 \end{bmatrix} = \begin{bmatrix} a_1d_1 & 0 & bd_1 & 0 \\ 0 & a_1d_2 & 0 & bd_2 \\ cd_1 & 0 & a_2d_1 & 0 \\ 0 & cd_2 & 0 & a_2d_2 \end{bmatrix}$$

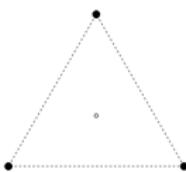
Tensor products of vector spaces are themselves vector spaces.

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

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IRs (cont.)

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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 .

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

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

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

Equivalence Classes

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$$g \rightarrow hgh^{-1}$$

In the space of a representation, this is referred to as a similarity transformation, which is essentially a change of basis.

Note that the number of equivalence classes N_c is equal to the number of irreducible representations.

$$N_{\text{IR}} = N_c$$

Character Tables

Irreducible representations are only unique up to change of basis, but their traces are invariant.

$$\chi^{(\alpha)}(g) = \text{Tr}(\rho^{(\alpha)}(g))$$

The trace of a representation is known as its character χ , which is unique for equivalence classes $\langle g \rangle$.

Example: C_4 Character Table

C_4	$\langle \mathbb{I} \rangle$	$\langle C_4 \rangle$	$\langle C_4^2 \rangle$	$\langle C_4^3 \rangle$
a_1	1	1	1	1
a_2	1	-1	1	-1
a_3	1	i	-1	$-i$
a_4	1	$-i$	-1	i

Characters are often displayed in 'character tables', with IRs on one axis and equivalence classes along the other.

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:

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

Orthogonality Theorems (cont.)

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Example: d-shell Splitting in Octohedral Coordinations

Take the Hydrogen-like orbitals $\psi_{\ell m}$ as a basis for spherically symmetric states. The d-shell orbitals are the basis functions of the $\ell = 2$ representations.

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

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Every representation of a group inherits a vector space on which it has a natural action. This vector space is spanned by a chosen set of basis functions $|\psi_i^\alpha\rangle$.

- ▶ An irrep Γ^α 's components are determined by basis:

$$\left(\Gamma^\alpha(g)\right)_i^j = \langle\psi_j^\alpha|\Gamma^\alpha(g)|\psi_i^\alpha\rangle$$

- ▶ Basis functions are said to “transform as an irrep α ” if:

$$\Gamma^\alpha(g)|\psi_i^\alpha\rangle = \sum_j \left(\Gamma^\alpha(g)\right)_i^j |\psi_j^\alpha\rangle$$

Basis Functions (cont.)

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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

Projection Operators

If we have an explicit form for IR α , we may project an arbitrary function onto the k -th basis function f_k^α of IR α with \hat{P}_α^{kk} :

$$\hat{P}_\alpha^{kk} = \frac{d_\alpha}{N} \sum_g [\Gamma_\alpha^{kk}(g)]^* O(g)$$

where d_α is the dimensional of IR α , and then we have:

$$f_\alpha^k(\vec{r}) = \hat{P}_\alpha^{kk} f(\vec{r})$$

From the characters alone, we may project a function onto it's total α subspace with \hat{P}_α :

$$\hat{P}_\alpha = \sum_k \hat{P}_\alpha^{kk} = \frac{d_\alpha}{N} \sum_g \chi^{(\alpha)*}(g) \hat{O}(g)$$

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 $U_{\alpha i \beta j}^{\gamma n}$ as:

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

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.

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

Coupling Coefficients (cont.)

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Dirl's Formula [dirl1979]:

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

Equivariant Functions

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

$$f(D^X(g)x) = D^Y(g)f(x)$$

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

Why Equivariant Functions?

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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.

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Why Equivariant Functions? (cont.)

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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?

Equivariant Networks

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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:

$$v_i^\alpha$$

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

Equivariant Networks (cont.)

Compositions of equivariant functions are equivariant [1].
We consider building blocks:

- ▶ Self-interaction:

$$v'_{nc} = W_c^i v_{ni}$$

- ▶ Non-linear functions along channels (for trivial irrep $\alpha = 1$):

$$v'_{nc} = f(v_{nc} + b_{nc})$$

- ▶ Group correlation with filters:

$$[F \star v](g) = \sum_{h \in G} \sum_c F_c(h) v_c(g^{-1}h)$$

- ▶ Tensor products with filters:

$$(v'_{nc})_n^\gamma = \sum_{ij} U_{\alpha i \beta j}^{\gamma n} (F_j^\beta \otimes V_i^\alpha)$$

- ▶ Pooling over nodes or channels:

$$v_c = \sum_n v_{nc}$$

$SO(3)$ Properties

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

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

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

Tensor Field Networks

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Tensor field networks [2] use $\text{SO}(3)$ 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
- ▶ $c_{\ell_f m_f \ell_i m_i}^{\ell m}$: 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.

Point Group Properties

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Groups of operations that leave at least one point fixed and are compatible with a Bravais lattice.

Point groups (in 3D) have following properties:

- ▶ 32 crystallographic point groups in 3D
- ▶ Finite number of irreps for each
- ▶ All irreps of point groups are of dimension $d_\alpha = 1, 2, 3$
- ▶ All allow a (often reducible) 3D representation
- ▶ Decompositions with $c_{\alpha\beta\gamma} = 0, 1, 2$

(Point group representations may be used to generate induced representations of space groups)

Site-symmetry Equivariant Networks

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

$$G = T \ltimes R$$

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

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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:

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

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

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Hamiltonian Group

We define the operator \hat{O}_G to be a representation of a group G that acts on H 's input space \vec{r} as:

$$\hat{O}_G(g)\hat{H}(\vec{r}) = \hat{H}(g^{-1}\vec{r})$$

The "group of the Hamiltonian" is the largest group of the form above that commutes with the Hamiltonian.

$$[\hat{H}, \hat{O}(g)] = 0 \quad \forall g \in G$$

In such a case, the operators must have a simultaneous set of eigenvectors ψ_α^k that span the space of functions:

$$f(\vec{r}) = \sum_{k,\alpha} c_k^\alpha \psi_\alpha^k = \sum_{k,\alpha} f_\alpha^k(\vec{r})$$

We have some freedom in choice of this set of basis functions on which the linear operators of the representations act.

Hydrogen Orbitals

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The Hydrogen Hamiltonian $\hat{H}_H(\vec{r})$ for a non-relativistic electron has separable eigenfunctions:

$$\psi_i(\vec{r}) = R_i(r)\Omega_i(\theta, \phi)$$

Furthermore, \hat{H}_H commutes with $SO(3)$ so these must be simultaneous with $SO(3)$:

$$[\hat{H}, \hat{O}(g)] = 0 \quad \forall g \in SO(3) \quad \Rightarrow \quad \psi_{nm}^\ell(\vec{r}) = R_n^\ell(r)Y_m^\ell(\theta, \phi)$$

(where R is also indexed by ℓ due to an 'accidental' symmetry)

- ▶ θ, ϕ dependence determined by group theory
- ▶ r dependence determined by specific form of \hat{H}_H

Tight-Binding Approximations

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In simplest form, consider H-like orbitals $|\psi_{nmp}^\ell\rangle$ localized at points p as basis for many particle system defined by \hat{H} so:

$$\hat{H}_{nmp\ell,jkhI} = \langle \psi_{jkh}^I | \hat{H} | \psi_{nmp}^\ell \rangle$$

- 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

- Incorporate point group symmetry of crystal and molecular sites by directly learning features associated with basis functions that transform as irreducible representations.
- Predict symmetry of properties *ab initio* but use machine learning for specific values
- Target data less clear, Wannier functions?

Maybe variational approach, minimize basic Hamiltonian?

References

- [1] Taco S. Cohen and Max Welling. *Group Equivariant Convolutional Networks*. 2016. arXiv: 1602.07576 [cs.LG]. URL: <https://arxiv.org/abs/1602.07576>.
- [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>.