Point Group Equivariant Convolutional Graph Neural Networks

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Groups and Vector Spaces

Representation Theory

Group Equivariant
Networks

Overview

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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 $\hat{x}, \hat{y}, \hat{z}$.

Often, we may construct new vector spaces from sets of known vector spaces.

Example: Functions on Real 3 Dimensional SpaceScalar 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.

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A group G is a set of elements $\{g_1,...,g_n\}$ with a binary operation $*:G\times G\to G$ 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. The general linear group is itself a vector space, and we may also form tensor products and direct sums of general linear group vectors.

Cartesian Products

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content...

 $K_V \oplus K_W$.

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Example: Direct Sum of Matrices

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

We may form direct sums $V \oplus W$ of vector spaces V, W by

distributivity to respective subspaces with a set of scalars

stipulating that the operation further enforces scalar

Direct sums of vector spaces are themselves vector spaces.

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We may construct tensor products $V \otimes W$ of vector spaces V, 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.

Example: 3D Representation of C_3

Consider three identical points:

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:

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

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

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

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

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

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

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Equivalence classes are subsets of group elements that mutually exchange under conjugation, where element g conjugated by element h means:

$$g o hgh^{-1}$$

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.

$$N_{IR} = N_c$$

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Representation

which is unique for equivalence classes $\langle g \rangle$. Example: C_4 Character Table

basis, but their traces are invariant.

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	-1	1	-1
a_3		i	-1	-i
a_4	1	-i	-1	i

Irreducible representations are only unique up to change of

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

The trace of a representation is known as it's character χ ,

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

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 coeffecients of expansion c_{α} as:

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

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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:

0	$\mid 1\langle \mathbb{I} angle$	$8\langle C_3 \rangle$	$3\langle C_2 \rangle$	$6\langle C_2' \rangle$	$6\langle C_4^3 \rangle$
$(d) \Gamma^{\ell=2}$	5	-1	1	1	$\overline{-1}$
A_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.

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Suppose we have some Hamiltonian group, so that the group operators $\hat{O}(g)$ commute with \hat{H} .

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

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.

The tight binding approximation often uses localized Hydrogen-like orbitals $\psi_{\it ellm}$ as a basis for many-body systems

Example: Group of a Hamiltonian

Consider a general Hamiltonian $\hat{H}(\vec{r})$ that depends only on the spatial coordinate \vec{r} of some particle. We then 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.

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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} :

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

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} :

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

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Consider a direct product decomposition of the irreps Γ :

$$\Gamma^{lpha}\Gamma^{eta}=igoplus_{\gamma}c_{lphaeta\gamma}\Gamma^{\gamma}$$

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:

$$\psi_{n}^{\gamma} = \sum_{i,i} U_{\alpha i\beta j}^{\gamma n} u_{i}^{\alpha} v_{j}^{\beta}$$

Example: Clebsch-Gordan Coefficients

The Clebsch-Gordan coefficients are the coupling coefficients of SO(3), which relate tensor product spaces of spherical harmonics to direct sums of spherical harmonics.

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Equivariant Functions

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

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

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SO(3) Equivariant Tensor Field Networks

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$$\left(v_{nc}^{L+1}\right)_{m}^{\ell} = v_{nc}^{L} + \sum_{b \in \mathcal{N}(n)} \sum_{\ell_{f}, m_{f}, \ell_{i}, m_{i}} c_{\ell_{f} m_{f} \ell_{i} m_{i}}^{\ell m} \left(F_{c}^{L}(r_{nb})\right)_{m_{f}}^{\ell_{f}} \left(v_{bc}^{L}\right)_{m_{i}}^{\ell_{i}}$$

Point Group

Theory

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- Take hydrogen-like orbitals and treat them as SO(3) features in e3nn.
- Allows for the learning of all rotational symmetries but doesn't enforce them from physical considerations.

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• Incorporate point group symmetry of crystal and molecular sites by directly learning features associated with basis functions that transform as irreducible representations.