Imperial College London

Exploring Group Equivariant Neural Networks using Set Partition Diagrams

Online Machine Learning Seminar

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Group Equivariant Neural Networks





Jellyfish: https://unsplash.com/photos/v-ti3sccORY

The Tale of Genji: https://www.amazon.co.uk/Tale-Genji-Vintage-Classics/dp/0679729534

Chapters in the Tale of Genji: Set Partitions

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Attribution: T. Piesk https://commons.wikimedia.org/wiki/File:Set_partitions_5;_list;_Genji_symbols.svg

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1. Review of Terminology

Neural networks consist of a **composition** of **layer functions**, where a layer function has the following typical form:



Physical processes often generate **data** that is high dimensional, and it can typically be represented in the form of a **high order tensor** (an element of $(\mathbb{R}^n)^{\otimes k}$) so that complex relationships can be captured between different features in the data.

Example: The adjacency matrix of a graph is a 2-order tensor

Graph	Matrix	Graph	Matrix
	$\begin{array}{cccccccccccccccccccccccccccccccccccc$		$\begin{array}{cccccccccccccccccccccccccccccccccccc$

The data often comes with a certain type of **symmetry** that is baked into the data itself: e.g

- **permutations** (labelling of a set, labelling of the vertices of a graph etc.)
- rotations (of the circle in the plane, of a sphere, etc.)
- translations (of an object in an image, etc.)

Symmetries in mathematics are given by groups.

A group is a non-empty set G together with a binary operation \bullet such that the following axioms are satisfied:

- **1** Closure: for all $g, h \in G$, $g \bullet h \in G$
- **2** Associativity: for all $g, h, k \in G$, $(g \bullet h) \bullet k = g \bullet (h \bullet k)$
- Identity: there exists a unique element e ∈ G such that, for all g ∈ G, g e = g = e g
- Inverses: for all g ∈ G, there exists an element h ∈ G such that g h = e = h g.

Examples of Groups

- the symmetric group S_n : permutations of $[n] \coloneqq \{1, \ldots, n\}$
- the **alternating** group A_n : subgroup of S_n consisting of all even permutations
- the general linear group GL(n): the group of all invertible transformations $\mathbb{R}^n \to \mathbb{R}^n$
- the special linear group SL(n): the subgroup of GL(n) consisting of all invertible transformations whose determinant is +1.
- the orthogonal group O(n): if we choose the standard basis of ℝⁿ, this is the subgroup of GL(n) consisting of matrices A such that A^TA = I_n
- the **special orthogonal** group SO(n): $O(n) \cap SL(n)$
- the symplectic group Sp(n), n = 2m: if we choose the symplectic basis of \mathbb{R}^n , this is the subgroup of GL(n) consisting of matrices A such that $A^{\top}JA = J$, where J is the block diagonal matrix consisting of m blocks of the form $\begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}$.

We are interested in **group actions**, where a group G acts on the elements of a set S, and, more specifically, if the elements of S index a basis of a vector space, then we are interested in **group representations**, which, in some sense, consider **groups as matrices**. This means that we can employ the tools of **linear algebra**.

Example: S_3 acts on $[3] = \{1, 2, 3\}$ by permutating its elements, and so, by indexing the standard basis $\{e_i\}$ of \mathbb{R}^3 by the elements of [3], we obtain a representation $S_3 \rightarrow GL(\mathbb{R}^3)$ that is given by $\sigma(e_i) = e_{\sigma(i)}$, and is extended linearly on the basis.

These are neural networks where the data lives in a vector space that is a representation of a group, and the maps are **equivariant** to the group:



If $\rho_V : G \to GL(V)$ and $\rho_W : G \to GL(W)$ are two representations of G, then $\phi : V \to W$ is said to be *G*-equivariant if, for all $g \in G$ and $v \in V$,

$$\phi(\rho_V(g)[v]) = \rho_W(g)[\phi(v)] \tag{1}$$

The set of all *linear* G-equivariant maps between V and W is denoted by $Hom_G(V, W)$, and, in particular, it forms a vector space.

2. Research Problem

Given the nature of the data that we wish to learn from, we are interested in group equivariant neural networks of the form:



G(n) is a subgroup of GL(n), and $(\mathbb{R}^n)^{\otimes k}$ is a representation of G(n) given by the diagonal action over the tensor product:

$$\rho_k(g)(v_1 \otimes \cdots \otimes v_k) \coloneqq gv_1 \otimes \cdots \otimes gv_k \tag{2}$$

for all $g \in G(n)$ and for all vectors $v_i \in \mathbb{R}^n$.

For different groups G(n), can we characterise all of the possible G(n)-equivariant, learnable, linear layers that appear in a G(n)-equivariant neural network where the layers are some tensor power of \mathbb{R}^n ?

In particular, can we find a basis or a spanning set of $\text{Hom}_{G(n)}((\mathbb{R}^n)^{\otimes k}, (\mathbb{R}^n)^{\otimes l})$ in the standard basis of \mathbb{R}^n ?



- Less training data is required: typically, the data does not need to be augmented.
- These architectures come with high levels of parameter sharing: hence, there are fewer parameters overall.
- Reduction in time, effort and cost needed to search for a neural network architecture: the form of the architectures is restricted by the symmetry group itself.
- (Crucially, as we will see) we do not need to decompose the representation spaces (ℝⁿ)^{⊗k} into irreducibles of G(n); hence there is no need for change of basis transformations into the Fourier domain.

3. Relevant Literature

Most Relevant Literature

- Zaheer et al. (2017), arXiv:1703.06114: introduced the first permutation equivariant neural network, called Deep Sets, for learning from sets in a permutation equivariant manner.
- Maron et al. (2019), arXiv:1812.09902: characterised all of the learnable, linear, equivariant layer functions when the layers are some tensor power of Rⁿ for the symmetric group S_n in the practical cases, by looking at fixed point equations representing the symmetric subspace.
- Sinzi et al. (2021), arXiv:2104.09459: constructed a numerical algorithm to find a basis to characterise the learnable, linear, equivariant layer functions when the layers are some tensor power of ℝⁿ for the orthogonal group O(n), special orthogonal group SO(n), and symplectic group Sp(n), but only for small values of n and for small orders of the tensors, since their algorithm runs out of memory on higher values.

4. Results

a) Symmetric Group S_n

We showed that there exists a bijective correspondence between



Pearce-Crump (2022): Connecting Permutation Equivariant Neural Networks and Partition Diagrams, arXiv:2212.08648, under review.

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Bijection between S_n orbits and Set Partitions

Let (I, J) be a class representative of an S_n orbit of $[n]^{l+k}$, where $l \in [n]^l$ and $j \in [n]^k$. Then, writing

$$(I, J) = (i_1, i_2, \dots, i_l, i_{l+1}, i_{l+2}, \dots, i_{l+k})$$
(3)

we define the bijection, for all $x, y \in [l + k]$, by

$$i_x = i_y \iff x, y$$
 are in the same block of π (4)

The bijection (4) is independent of the choice of class representative since

$$i_x = i_y \iff \sigma(i_x) = \sigma(i_y) \text{ for all } \sigma \in S_n$$
 (5)

Notice that the LHS of (4) is checking for an equality on the elements of [n], whereas the RHS is separating the elements of [l + k] into blocks; hence π must have at most n blocks.

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Example 1: End_{S4}(\mathbb{R}^4) (n = 4, k = 1, l = 1)

Set Partition Diagram	Partition π	Block Labelling $(I_{\pi} \mid J_{\pi})$	Standard Basis Element X_{π}
	$\{1, 2\}$	$\{1 \mid 1\}$	$ \begin{array}{cccccccccccccccccccccccccccccccccccc$
	$\{1 \mid 2\}$	$\{1 \mid 2\}$	$ \begin{array}{cccccccccccccccccccccccccccccccccccc$

Example 2: Hom_{S_2}((\mathbb{R}^2)^{$\otimes 2$}, \mathbb{R}^2) (n = 2, k = 2, l = 1)

Set Partition Diagram	Partition π	$\begin{array}{c} Block \ Labelling\\(I_\pi \mid J_\pi)\end{array}$	Standard Basis Element X_{π}
	$\{1, 2, 3\}$	$\{1\mid 1,1\}$	$\begin{bmatrix} 1,1 & 1,2 & 2,1 & 2,2 \\ 1 & 0 & 0 & 0 \\ 2 & 0 & 0 & 0 & 1 \end{bmatrix}$
	$\{1,2 \mid 3\}$	$\{1\mid 1,2\}$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$
	$\{1,3 \mid 2\}$	$\{1\mid 2,1\}$	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$
	$\{1 \mid 2, 3\}$	$\{1 \mid 2, 2\}$	$\begin{bmatrix} 1,1 & 1,2 & 2,1 & 2,2 \\ 1 & 0 & 0 & 1 \\ 2 & 1 & 0 & 0 & 0 \end{bmatrix}$

- Martin (1990, 1994, 1996): first introduced the partition algebra P_k(n) upon which these results are based.
- Jones (1994): developed a surjective homomorphism between the partition algebra and the centraliser algebra on a k-order tensor of Rⁿ.
- Benkart and Halverson (2019), arXiv:1709.07751: showed how the partition algebra can be used to construct the invariant theory of the symmetric group.

b) Orthogonal Group O(n), Special Orthogonal Group SO(n), Symplectic Group Sp(n)

We showed that, for O(n) and Sp(n), there exists a bijective correspondence between



and, for SO(n), there exists a bijective correspondence between



Pearce-Crump (2022): Brauer's Group Equivariant Neural Networks, arXiv:2212.08630, ICML 2023 (live oral presentation).

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Brauer's Invariant Argument

It can be shown that

$$C = \sum_{I \in [n]^{I}, J \in [n]^{k}} C_{I,J} E_{I,J}$$
(6)

is an element of $\text{Hom}_{G(n)}((\mathbb{R}^n)^{\otimes k}, (\mathbb{R}^n)^{\otimes l})$ (having chosen some basis of \mathbb{R}^n) if and only if the function

$$(\mathbb{R}^n)^{\otimes l+k} \to \mathbb{R} \tag{7}$$

which maps an element of the form

$$u(1) \otimes u(2) \otimes \cdots \otimes u(l) \otimes v(1) \otimes v(2) \otimes \cdots \otimes v(k)$$
(8)

to

$$\sum_{I \in [n]^{I}, J \in [n]^{k}} C_{I,J} \prod_{t=1}^{I} u_{i_{t}}(t) \prod_{r=1}^{k} v_{j_{r}}(r)$$
(9)

is an invariant for the group G(n).

Suppose that \mathbb{R}^n has associated with it a non-degenerate, symmetric, bilinear form (\cdot, \cdot) .

Pick the standard basis for \mathbb{R}^n , so that (\cdot, \cdot) becomes the Euclidean inner product on \mathbb{R}^n .

If $f: (\mathbb{R}^n)^{\otimes (l+k)} \to \mathbb{R}$ is a polynomial function on elements in $(\mathbb{R}^n)^{\otimes (l+k)}$ of the form

$$u(1) \otimes u(2) \otimes \cdots \otimes u(l) \otimes v(1) \otimes v(2) \otimes \cdots \otimes v(k)$$
(10)

that is O(n)-invariant, then f must be a polynomial of the Euclidean inner products

$$(u(i), u(j)), (u(i), v(j)), (v(i), v(j))$$
(11)

Hence, from Brauer's Invariant Argument, we get that

Theorem (Spanning Set of Invariants $(\mathbb{R}^n)^{\otimes (l+k)} \to \mathbb{R}$ for O(n))

The functions

$$(z(1), z(2))(z(3), z(4)) \dots (z(l+k-1), z(l+k))$$
(12)

where $z(1), \ldots, z(l+k)$ is a permutation of

$$u(1), u(2), \ldots, u(l), v(1), v(2), \ldots, v(k)$$

form a spanning set of invariants $(\mathbb{R}^n)^{\otimes (l+k)} \to \mathbb{R}$ for O(n).

Example 1: $\text{End}_{O(2)}((\mathbb{R}^2)^{\otimes 2})$ (n = 2, k = 2, l = 2)

Set Partition Diagram	Inner Products	Spanning Set Element
	(u(1), u(2))(v(1), v(2))	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$
	(u(1), v(1))(u(2), v(2))	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$
	(u(1), v(2))(u(2), v(1))	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$

First Fundamental Theorem for Sp(n)

Suppose that \mathbb{R}^n (n = 2m) has associated with it a non-degenerate, skew-symmetric, bilinear form $\langle \cdot, \cdot \rangle$.

Choosing the symplectic basis

$$\widetilde{B} \coloneqq \{e_1, e_{1'}, \dots, e_m, e_{m'}\}$$
(13)

for \mathbb{R}^n , where the *i*th basis vector in the set has a 1 in the *i*th position and a 0 elsewhere, which satisfies the relations

$$\langle e_{\alpha}, e_{\beta} \rangle = \langle e_{\alpha'}, e_{\beta'} \rangle = 0$$
 (14)

$$\langle e_{\alpha}, e_{\beta'} \rangle = -\langle e_{\alpha'}, e_{\beta} \rangle = \delta_{\alpha,\beta}$$
 (15)

we have that $\langle\cdot,\cdot\rangle$ becomes the skew product

$$\langle x, y \rangle = \sum_{r=1}^{m} (x_r y_{r'} - x_{r'} y_r) = \sum_{i,j} \langle e_i, e_j \rangle x_i y_j$$
(16)

for all $x, y \in \mathbb{R}^n$.

Note that, in this basis, the non-degenerate, symmetric, bilinear form (\cdot, \cdot) which we can also associate with \mathbb{R}^n , becomes the Euclidean inner product on \mathbb{R}^n since the symplectic basis is standard with respect to (\cdot, \cdot) .

Then, if $f : (\mathbb{R}^n)^{\otimes (l+k)} \to \mathbb{R}$ is a polynomial function on elements in $(\mathbb{R}^n)^{\otimes (l+k)}$ of the form

$$u(1) \otimes u(2) \otimes \cdots \otimes u(l) \otimes v(1) \otimes v(2) \otimes \cdots \otimes v(k)$$
(17)

that is Sp(n)-invariant, then f must be a polynomial of the Euclidean inner products

$$(u(i), v(j))$$
 (18)

together with the skew products

$$\langle u(i), u(j) \rangle, \langle v(i), v(j) \rangle$$
 (19)

such that i < j in (19).

Hence, from Brauer's Invariant Argument, we get that

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Theorem (Spanning Set of Invariants $(\mathbb{R}^n)^{\otimes (l+k)} \to \mathbb{R}$ for Sp(n), n = 2m)

The functions

$$[z(1), z(2)][z(3), z(4)] \dots [z(l+k-1), z(l+k)]$$
(20)

where $z(1), \ldots, z(l+k)$ is a permutation of

 $u(1), u(2), \ldots, u(l), v(1), v(2), \ldots, v(k)$

and

$$[z(i), z(i+1)] := \begin{cases} if \ z(i) = u(j) \ and \ z(i+1) = v(m), \\ (z(i), z(i+1)) & or \ z(i) = v(m) \ and \ z(i+1) = u(j), \\ for \ some \ j \in [I], \ m \in [k] \\ \langle z(i), z(i+1) \rangle & otherwise. \end{cases}$$

$$(21)$$

form a spanning set of invariants $(\mathbb{R}^n)^{\otimes (l+k)} \to \mathbb{R}$ for Sp(n), with n = 2m.

Example 2: $End_{Sp(2)}((\mathbb{R}^2)^{\otimes 2})$ (n = 2, k = 2, l = 2)

Set Partition Diagram	Inner/Skew Products	Spanning Set Element
$ \begin{array}{c} 1 \\ 0 \\ 0 \\ 0 \\ 3 \\ 4 \end{array} $	$\langle u(1), u(2) \rangle \langle v(1), v(2) \rangle$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$
	(u(1), v(1))(u(2), v(2))	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$
	(u(1), v(2))(u(2), v(1))	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$

First Fundamental Theorem for SO(n)

Suppose that \mathbb{R}^n has associated with it a non-degenerate, symmetric, bilinear form (\cdot, \cdot) . Choose the standard basis for \mathbb{R}^n , so that (\cdot, \cdot) becomes the Euclidean inner product on \mathbb{R}^n .

If $f: (\mathbb{R}^n)^{\otimes (l+k)} \to \mathbb{R}$ is a polynomial function on elements in $(\mathbb{R}^n)^{\otimes (l+k)}$ of the form

$$u(1) \otimes u(2) \otimes \cdots \otimes u(l) \otimes v(1) \otimes v(2) \otimes \cdots \otimes v(k)$$
(22)

that is SO(n)-invariant, then it must be a polynomial of the Euclidean inner products

$$(u(i), u(j)), (u(i), v(j)), (v(i), v(j))$$
(23)

together with the $n \times n$ subdeterminants of the $n \times (l + k)$ matrix M having as its columns:

$$M := \begin{pmatrix} | & | & | & | & | & | & | \\ u(1) & u(2) & \dots & u(l) & v(1) & v(2) & \dots & v(k) \\ | & | & | & | & | & | & | \end{pmatrix}$$
(24)

Hence, from Brauer's Invariant Argument, we get that

Theorem (Spanning Set of Invariants $(\mathbb{R}^n)^{\otimes (l+k)} \to \mathbb{R}$ for SO(n))

Functions of the form

$$(z(1), z(2))(z(3), z(4)) \dots (z(l+k-1), z(l+k))$$
(25)

together with functions of the form

det(z(1),...,z(n))(z(n+1),z(n+2))...(z(l+k-1),z(l+k))(26)

where $z(1), \ldots, z(l+k)$ is a permutation of

 $u(1), u(2), \ldots, u(l), v(1), v(2), \ldots, v(k)$

form a spanning set of invariants $(\mathbb{R}^n)^{\otimes (l+k)} \to \mathbb{R}$ for SO(n).

Example 3: Hom_{SO(2)}($(\mathbb{R}^2)^{\otimes 3}, \mathbb{R}^2$) (n = 2, k = 3, l = 1)

Set Partition Diagram	Inner Products	Spanning Set Element	
	(u(1), v(1))(v(2), v(3))	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	
	(u(1), v(2))(v(1), v(3))	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	
	(u(1), v(3))(v(1), v(2))	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	

Set Partition Diagram	Inner Products	Spanning Set Element	
	$\det(v(2),v(3))(u(1),v(1))$	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	
	$\det(v(1),v(3))(u(1),v(2))$	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	
	$\det(v(1),v(2))(u(1),v(3))$	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	

Set Partition Diagram	Inner Products	Spanning Set Element
	$\det(u(1),v(3))(v(1),v(2))$	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$
	$\det(u(1),v(2))(v(1),v(3))$	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$
	$\det(u(1),v(1))(v(2),v(3))$	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$

- Brauer (1937): first introduced the Brauer algebra for the purpose of understanding the centraliser algebras of the groups O(n), SO(n) and Sp(n)
- Grood (1999): investigated the representation theory of the Brauer–Grood algebra

We showed that there exists a bijective correspondence between



Pearce-Crump (2023): How Jellyfish Characterise Group Equivariant Neural Networks, arXiv:2301.10152, ICML 2023 (poster presentation).

The set partitions that correspond to more than one A_n orbit are said to **split**.

The basis elements corresponding to set partitions that do not split can be found in exactly the same way as for the symmetric group S_n .

To find the basis elements corresponding to set partitions that split, we use *n*-legged **jellyfish**



which correspond to the **determinant map** $(\mathbb{R}^n)^{\otimes n} \to \mathbb{R}$ defined on the standard basis by

$$e_I \coloneqq e_{i_1} \otimes \cdots \otimes e_{i_n} \mapsto \begin{vmatrix} e_{i_1} & \dots & e_{i_n} \end{vmatrix}$$
 (27)

From before: Hom_{S_2}((\mathbb{R}^2)^{$\otimes 2$}, \mathbb{R}^2) (n = 2, k = 2, l = 1)

Set Partition Diagram	Partition π	$\frac{Block Labelling}{(I_\pi \mid J_\pi)}$	Standard Basis Element X_{π}
	$\{1, 2, 3\}$	$\{1\mid 1,1\}$	$\begin{bmatrix} 1,1 & 1,2 & 2,1 & 2,2 \\ 1 & 0 & 0 & 0 \\ 2 & 0 & 0 & 0 & 1 \end{bmatrix}$
	$\{1,2 \mid 3\}$	$\{1\mid 1,2\}$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$
	$\{1,3 \mid 2\}$	$\{1\mid 2,1\}$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$
	$\{1 \mid 2, 3\}$	$\{1\mid 2,2\}$	$\begin{bmatrix} 1,1 & 1,2 & 2,1 & 2,2 \\ 1 & 0 & 0 & 1 \\ 2 & 1 & 0 & 0 & 0 \end{bmatrix}$

What about $\operatorname{Hom}_{\mathcal{A}_2}((\mathbb{R}^2)^{\otimes 2}, \mathbb{R}^2)$?

We follow the **procedure** given below (for **general** n, k, l):

1. Check which of the (k, l)-set partition diagrams appearing in the S_n case split and which do not. In this case, all four (2, 1)-set partition diagrams split.

2. For those that do not split, the basis matrix is the same as for the S_n case.

3. Otherwise, we construct a **jellyfish diagram** for each (k, l)-set partition diagram that **splits**, as follows: first, we flatten it, maintaining the order of the vertices, then we add a new top row of *n* vertices and connect the lowest numbered vertex in each block *i* to vertex *i* in the top row, and finally we attach an *n*-legged jellyfish to the top row of vertices.

For example, for the second set partition diagram



we obtain the following jellyfish diagram:



We can show that the jellyfish diagram corresponds to a **map** in $\operatorname{Hom}_{A_n}((\mathbb{R}^n)^{\otimes l+k}, \mathbb{R})$ that sends standard basis vectors indexed by the elements of the S_n orbit that corresponds to the original (k, l)-set partition diagram to ± 1 , and to 0 otherwise.

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4. We then calculate the **two** A_n **orbits** that the S_n orbit **splits into**, using the **possible outcomes** of the **map** on standard basis vectors indexed by its elements, namely ± 1 , as **separate classes**.

For the jellyfish diagram given above, as the S_2 orbit is $\{(1,1,2), (2,2,1)\}$, the map takes $e_{(1,1,2)}$ to +1 and $e_{(2,2,1)}$ to -1. Hence the S_2 orbit splits into two A_2 orbits, namely $\{(1,1,2)\}$ and $\{(2,2,1)\}$.

5. Finally, we obtain the two basis matrices X^+ and X^- , each of which is a sum of the matrix units in Hom $((\mathbb{R}^n)^{\otimes k}, (\mathbb{R}^n)^{\otimes l})$ that are indexed by the elements of the A_n orbits.

For our example, we have that $X^+ = E_{(1|1,2)}$ and $X^- = E_{(2|2,1)}$

Example: Hom_{A_2}((\mathbb{R}^2)^{$\otimes 2$}, \mathbb{R}^2) (n = 2, k = 2, l = 1)

Set Partition Diagram	Partition π	Standard Basis Element X^+_{π}	Standard Basis Element X_{π}^{-}
	$\{1, 2, 3\}$	$\begin{bmatrix} 1,1 & 1,2 & 2,1 & 2,2 \\ 1 & 1 & 0 & 0 & 0 \\ 2 & 0 & 0 & 0 & 0 \end{bmatrix}$	$\begin{bmatrix} 1,1 & 1,2 & 2,1 & 2,2 \\ 1 & 0 & 0 & 0 & 0 \\ 2 & 0 & 0 & 0 & 1 \end{bmatrix}$
	$\{1,2 \mid 3\}$	$\begin{bmatrix} 1,1 & 1,2 & 2,1 & 2,2 \\ 1 & 0 & 1 & 0 & 0 \\ 2 & 0 & 0 & 0 & 0 \end{bmatrix}$	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$
	$\{1,3 \mid 2\}$	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$
	$\{1 \mid 2, 3\}$	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$

- Bloss (2005): studied the centraliser algebra of the alternating group, adapting the result of Jones (1994) for that of the symmetric group.
- Comes (2020), arXiv:1612.05182: largely determined the theory of alternating group A_n equivariance; however, they relied heavily on the language of category theory in their exposition.

- Pearce-Crump (2023): Categorisation of Group Equivariant Neural Networks, arXiv:2304.14144, under review: developed a category theoretic framework around the characterisations given above, leading to:
- Pearce-Crump (2023): An Algorithm for Computing with Brauer's Group Equivariant Neural Network Layers, arXiv:2304.14165, under review: allows us to compute with the layers characterised in Brauer's Group Equivariant Neural Networks in a faster way, using decompositions into Kronecker product matrices.

5. Closing Remarks

- Given the current **limitations of hardware**, tensor product neural networks require **significant engineering efforts** in order to achieve the required scale
- This is because storing high-order tensors in memory is not a straightforward task.
- This was demonstrated by Kondor et al. (2018), who had to develop **custom CUDA kernels** in order to implement their tensor product based neural networks.

- Nevertheless, we anticipate that with the increasing availability of computing power, **higher-order** group equivariant neural networks will become **more prevalent** in practical applications.
- Notably, while the dimension of tensor power spaces increases exponentially with their order, the **dimension** of the space of equivariant maps between such tensor power spaces is often much **smaller**, and the corresponding **matrices** are typically **sparse**.
- Therefore, while storing these matrices may present some technical difficulties, it should be feasible with the current computing power that is available.