Or: Beyond linearity

AcceptChange what you cannot changeaccept



I report on work of Gibson and Williamson



► Task: Identify handwritten digits

- ► We can see this as a function in the following way:
 - \blacktriangleright Convert the pictures into grayscale values, e.g., 28 \times 28 grid of numbers
 - ▶ Flatten the result into a vector, e.g., $28 \times 28 \mapsto$ a vector with $28^2 = 784$ entries
 - ▶ The output is a vector with 10 entries
- ▶ We thus have a function $\mathbb{R}^{784} \to \mathbb{R}^{10}$





- Idea: Approximate the unknown function $\mathbb{R}^{784} \to \mathbb{R}^{10}$
- ▶ NN: A piecewise linear (PL) approximation (matrices + PL maps)
- ► The matrices represent numbers (weights) and offsets (biases; mostly ignored today)
- ► The PL maps are usually ReLUs (rectified linear unit)





▶ The task of an NN is to approximate an unknown function

▶ It consists of neurons = entries of vectors, and weights = entries of matrices







July 2024

2 / 5

What is an Equivariant Neural Network (ENN)?



► Task Learn a map that is equivariant with respect to some symmetry

Examples

- Image recognition is often invariant under translation; for example, whether ice cream is present in an image should not depend on the position of the ice cream in the image
- ▶ Point cloud problems are invariant under the symmetric group

What is an Equivariant Neural Network (ENN)?



Periodic images, say *n*-by-*n* pixels, have an action of $C_n^2 = (\mathbb{Z}/n\mathbb{Z})^2$ by translation

In math, a periodic image is an element of $V = \operatorname{Fun}(C_n^2, \mathbb{R})$ (maps $C_n^2 \to \mathbb{R}$) The standard action on V is the shift above: $((a, b) \subset f)(x, y) = f(x + a, y + b)$

position of the ice cream in the image

▶ Point cloud problems are invariant under the symmetric group



Or: Beyond linearity

What is an Equiv

By the way

\boldsymbol{c} is an example of what convolution usually does



Task	Lear	'n
Examples		
 Image re whether position 		
► P	oint	clo

Operation	Filter	Convolved Image
Identity	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	C.
	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
Edge detection	$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	
Sharpen	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
Box blur (normalized)	$\frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$	C.
Gaussian blur (approximation)	$\frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$	C.



c group

What is an Equivariant Neural Network (ENN)?



Enter, rep theory All involved spaces are reps, all maps equivariant

Rep theory questions

- ► Can we decompose the network into smaller ("simple") bits?
- ► The space of all weights is much smaller than for a vanilla NN: can we use rep theory to study the involved maps?



Or: Beyond linearity



• Let
$$C_n = \mathbb{Z}/n\mathbb{Z} = \langle a | a^n = 1 \rangle$$

- ▶ The simple complex C_n -reps are given by the *n*th roots of unity L_{z^k}
- What about the simple real C_n -reps?

Equivariant neural networks and representation theory

Or: Beyond linearity



► For $\Theta = 2\pi/n$ observe that

$$\begin{pmatrix} \exp(ik\Theta) & 0\\ 0 & \overline{\exp(ik\Theta)} \end{pmatrix} \sim_{\mathbb{C}} \begin{pmatrix} \cos(k\Theta) & -\sin(k\Theta)\\ \sin(k\Theta) & \cos(k\Theta) \end{pmatrix}$$

▶ ⇒ the simple real C_n -reps are $L_0 = L_{z^0}$, $L_1 = L_{z^1} \oplus \overline{L_{z^1}}$, etc.



For $\Theta = 2\pi/n$ observe that

$$\begin{pmatrix} \exp(ik\Theta) & 0\\ 0 & \exp(ik\Theta) \end{pmatrix} \sim_{\mathbb{C}} \begin{pmatrix} \cos(k\Theta) & -\sin(k\Theta) \\ \sin(k\Theta) & \cos(k\Theta) \end{pmatrix}$$

▶ ⇒ the simple real C_n -reps are $L_0 = L_{z^0}$, $L_1 = L_{z^1} \oplus \overline{L_{z^1}}$, etc.



Thus, we can (explicitly) decompose $\mathbb{R}[C_n] \cong L_0 \oplus L_1 \oplus ...$ and compute

$$L_{i} \xrightarrow{incl.} \mathbb{R}[C_{n}] \xrightarrow{ReLU} \mathbb{R}[C_{n}] \xrightarrow{proj.} L_{1}$$

PL rep theory (of cyclic groups)



► Interaction graph Γ vertices = simples, edges = nonzero maps $L_i \rightarrow L_j$ ► This is a measurement of difficulty : a lot of ingoing arrows = hard Equivariant neural networks and representation theory Or: Beyond linearity July 2024 4 / 5



► Interaction graph Γ vertices = simples, edges = nonzero maps $L_i \rightarrow L_j$ ► This is a measurement of difficulty : a lot of ingoing arrows = hard Equivariant neural networks and representation theory Or: Beyond linearity July 2024

4 / 5











▶ There are many PL maps, i.e. for *G*-representations *V*, *W* we have $\hom_{G}^{p'}(V, W) = 0 \text{ or } \dim_{\mathbb{R}} \hom_{G}^{p'}(V, W) > |\mathbb{N}|$

Schur's lemma is maximally false, i.e. let L and K be two simple real G-representations with actions maps ρ_L and ρ_K . Then:

$$\hom_{\mathcal{G}}^{pl}(L, \mathcal{K}) \neq 0 \iff \ker(\rho_L) \subset \ker(\rho_{\mathcal{K}}).$$

Any PL activation map has an interaction graph Γ equal to the one of:

ReLU or Abs or Id

Thus, Γ depends only on G (up to 3 states it takes)



- ► Linear map representation theory 👐 Fourier approximation of sin
- ► Higher frequencies ↔ simples with a lot of ingoing arrows

Equivariant neural networks and representation theory

Or: Beyond linearity















This is a measurement of difficulty: a lot of ingoing arrows = hard Reductor and about an apparentic facty in Report South Aug 2601 A / 5

There is still much to do...



















► This is a measurement of difficulty: a lot of ingoing arrows = hard spatie was about at spanness may be byen basis.









Thanks for your attention!