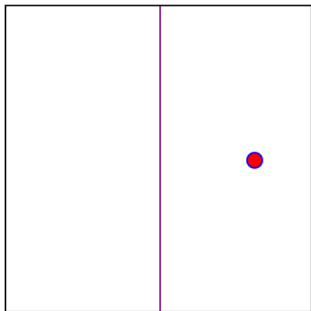


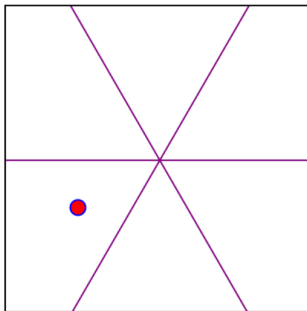
Piecewise linear representation theory

Or: Non-linear, but still rep theory

Accept **Change** what you cannot **change** **accept**



$$L_0 = L_{triv}, \text{ord}(a) = 1$$



$$L_1, \text{ord}(a) = 3$$

I report on work of Joel Gibson and Geordie Williamson

July 2023

Problem involving

an action

$$G \curvearrowright X$$

new
insights?

.....→

Problem involving

a linear action

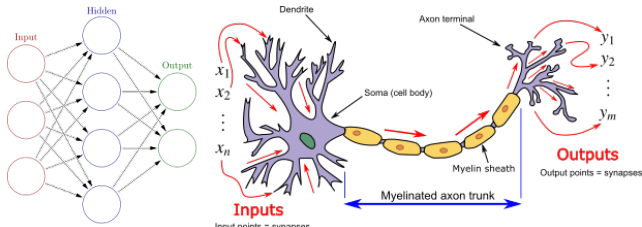
$$\mathbb{K}[G] \curvearrowright \mathbb{K}X$$

“Decomposition of
the problem”

$$\mathbb{K}[G] \curvearrowright \bigoplus V_i$$

- ▶ Representation theory approach Decompose a problem into simples and take it from there
- ▶ Today Representation theory applied to machine learning

Learning with piecewise linear maps



Vanilla neural net:

$$\phi: \mathbb{R}^{n_1} \xrightarrow{\phi_1} \mathbb{R}^{n_2} \xrightarrow{\phi_2} \mathbb{R}^{n_3} \xrightarrow{\phi_3} \mathbb{R}^{n_4} \xrightarrow{\phi_4} \mathbb{R}^{n_5} \xrightarrow{\phi_5} \mathbb{R}^{n_5}$$

"ReLU"

Each "layer" is: $\mathbb{R}^{n_i} \xrightarrow[\text{(or affine linear)}]{\text{linear}} \mathbb{R}^{n_{i+1}} \xrightarrow[\text{max}(0, -)]{\text{coordinatewise}} \mathbb{R}^{n_{i+1}}$

- ▶ Neural network "=" a sequence of maps $\mathbb{R}^{n_1} \xrightarrow{\phi_1} \mathbb{R}^{n_2} \xrightarrow{\phi_2} \dots \xrightarrow{\phi_k} \mathbb{R}^{n_{k+1}}$
- ▶ Deep = many layers Crucial 1 #layers \leftrightarrow accuracy of the result

Example (picture recognition)



Are we seeing ice cream? Yes, maybe or no?

Neural ice cream network:

$f: \mathbb{R}^{\#pixels} \rightarrow \text{layers} \rightarrow \mathbb{R}$ and $f(\mathbb{R}^{\#pixels}) \rightsquigarrow$ probability of seeing ice cream

▶ Neural network = a sequence of maps $\mathbb{R}^{n_1} \rightarrow \mathbb{R}^{n_2} \rightarrow \dots \rightarrow \mathbb{R}$

Crucial 1 #layers \rightsquigarrow accuracy of the result

▶ Deep = many layers \rightsquigarrow accuracy of the result

Example (picture recognition with group action)

S_n permutes the birds



If our problem at hand has some group symmetry
then we should be able to use the representation theory approach, right?

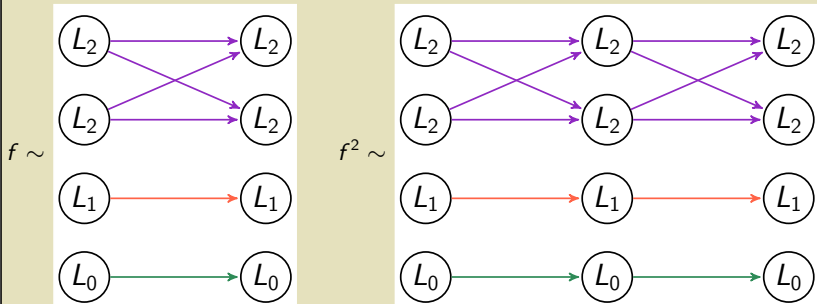
► **Deep** — many layers **Crucial 1** #layers \leftrightarrow accuracy of the result

Learning with piecewise linear maps

Why is that potentially amazing? Well:

Assume we want to know f^k for linear G -equivariant $f: V \rightarrow V$

The representation theory approach plus Schur's lemma give

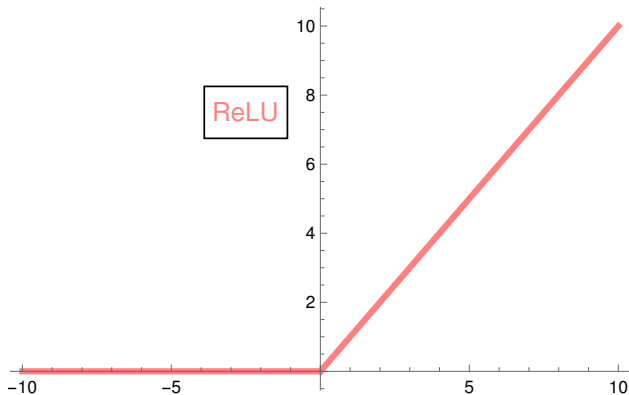


$\Rightarrow f^k$ is pretty easy to compute

► Neural network = a sequence of maps $\mathbb{R} \rightarrow \mathbb{R} \rightarrow \dots \rightarrow \mathbb{R}$

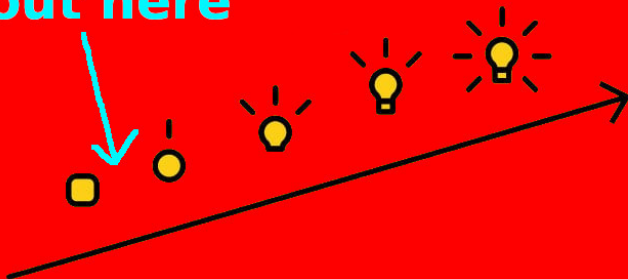
► Deep = many layers Crucial 1 #layers \leftrightarrow accuracy of the result

Learning with piecewise linear maps



- ▶ $ReLU: \mathbb{R} \rightarrow \mathbb{R}, x \mapsto \max(x, 0)$ is the most popular activator map in machine learning
- ▶ Linear maps are not working [Play live at https://playground.tensorflow.org](https://playground.tensorflow.org)
- ▶ **Crucial 2** Machine learning likes piecewise linear but non-linear maps

We are about here



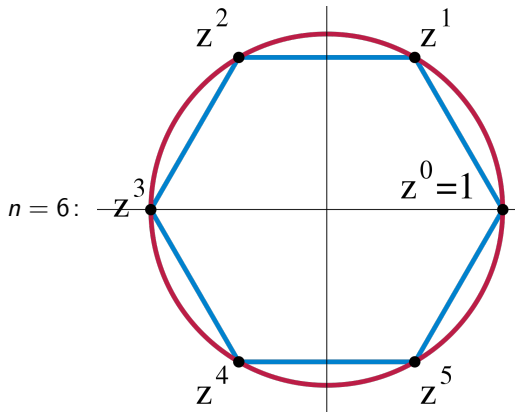
Crucial 1 #layers \leftrightarrow accuracy of the result

▶ Crucial 2 Machine learning likes piecewise linear but non-linear maps

▶ \Rightarrow study piecewise linear representation theory

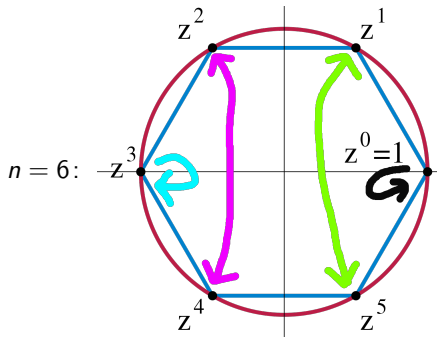
▶ I show you a few teeny-weeny steps in this direction!

Let us study cyclic groups



- ▶ Let $C_n = \mathbb{Z}/n\mathbb{Z} = \langle a \mid a^n = 1 \rangle$
- ▶ 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?

Let us study cyclic groups

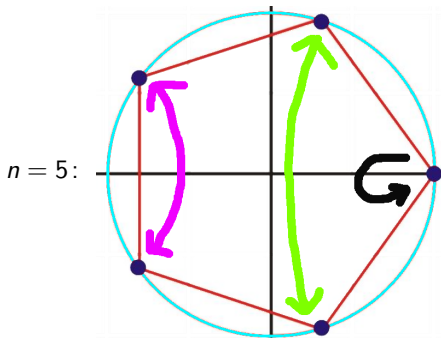


► For $\Theta = 2\pi/n$ observe that

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

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

Let us study cyclic groups



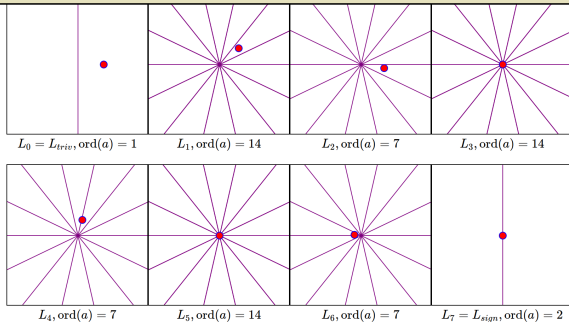
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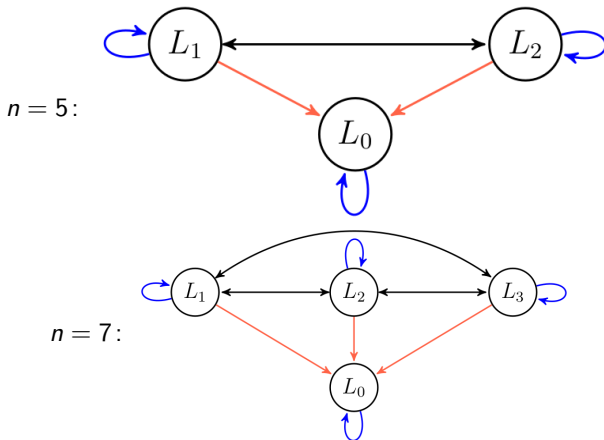
Play live at <https://www.dtubbenhauer.com/pl-reps/site/index.html>



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

$$L_i \xrightarrow{\text{incl.}} \mathbb{R}[C_n] \xrightarrow{\text{ReLU}} \mathbb{R}[C_n] \begin{array}{l} \xrightarrow{\text{proj.}} L_0 \\ \xrightarrow{\text{proj.}} L_1 \\ \xrightarrow{\text{proj.}} \vdots \end{array}$$

Let us study cyclic groups

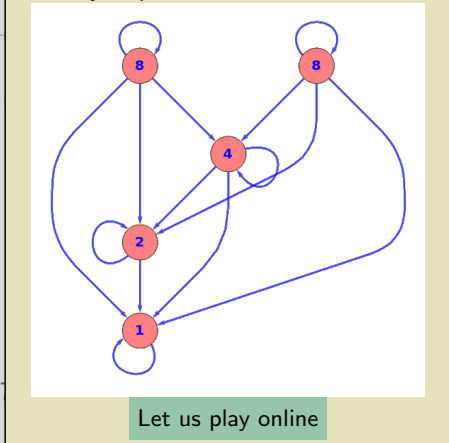


- ▶ Interaction graph Γ vertices = simples, edges = nonzero maps $L_i \rightarrow L_j$
- ▶ This is a measurement of difficulty : a lot of ingoing arrows = hard

Let us study cyclic

It is easy to produce these with a machine

$n = 5$:



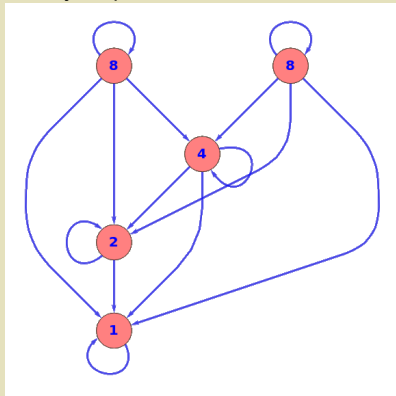
$n =$

- ▶ Interaction graph Γ vertices = simples, edges = nonzero maps $L_i \rightarrow L_j$
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It is easy to produce these with a machine

$n = 5$:



$n =$

Let us play online

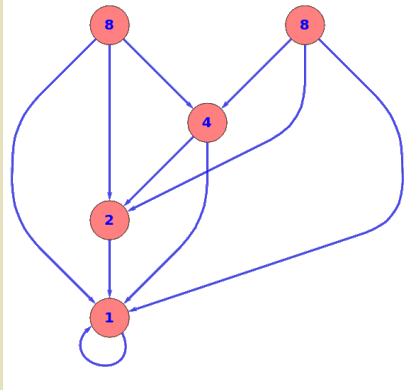
$ord(L_i)$ = order of the action of a
 $ord'(L_i)$ = same but divide by two if $ord(L_i)$ is even

Theorem (for ReLU)

Every vertex has a loop and there is a non-loop edge from L to K in Γ if and only if $ord(K)$ divides $ord'(L)$

Let us study

It is easy to produce these with a machine – for any map



This is now the absolute value

$ord(L_i) =$ order of the action of a
 $ord'(L_i) =$ same but divide by two if $ord(L_i)$ is even

Theorem (for Abs)

There is a non-loop edge from L to K in Γ
if and only if $ord(K)$ divides $ord'(L)$

► Interaction

► This is a m

aps $L_i \rightarrow L_j$

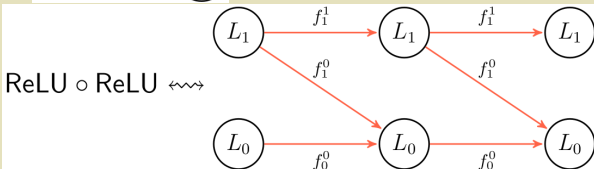
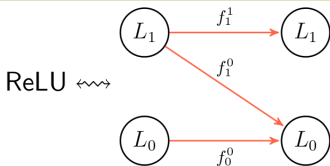
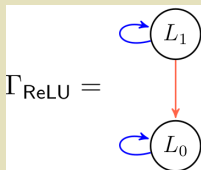
= hard

Let us study cyclic groups

Calculation complexity is captured in Γ :

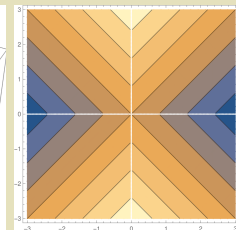
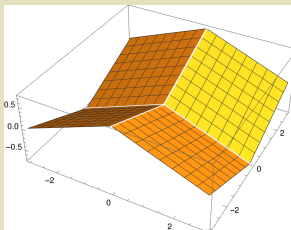
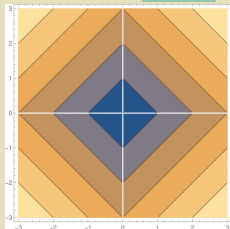
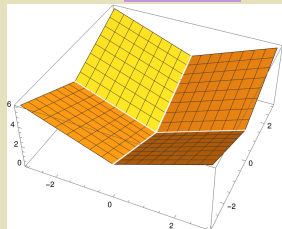
Theorem

calcs needed to evaluate f^k on L_i = number of length k path ending at L_i in Γ_f



- ▶ 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

The piecewise linear but **non-linear** maps from L_1 to **trivial** and **sign** are:

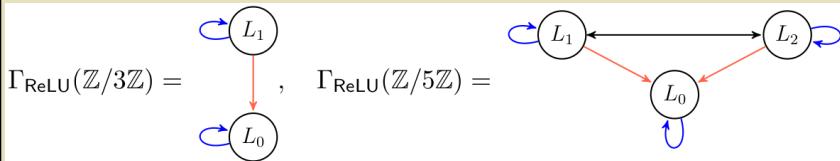


Let us play online

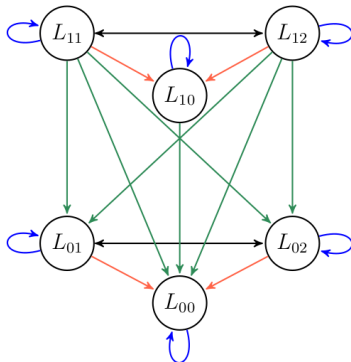


-
- ▶ Finite abelian groups
 - ▶ Dihedral groups
 - ▶ Symmetric groups
 - ▶ Products of these

Finite abelian group = products of cyclic groups



$\Rightarrow \Gamma_{\text{ReLU}}(\mathbb{Z}/3\mathbb{Z} \times \mathbb{Z}/5\mathbb{Z}) =$



Its just the product

Honorable

Theorem

For a general piecewise linear map $f: \mathbb{R} \rightarrow \mathbb{R}$:

(a) If f is linear, then Γ is trivial

(b) If $f = \text{Abs}$, then Γ is as before

(c) Otherwise Γ is as for *ReLU*

▶ Finite abelian groups

▶ Dihedral

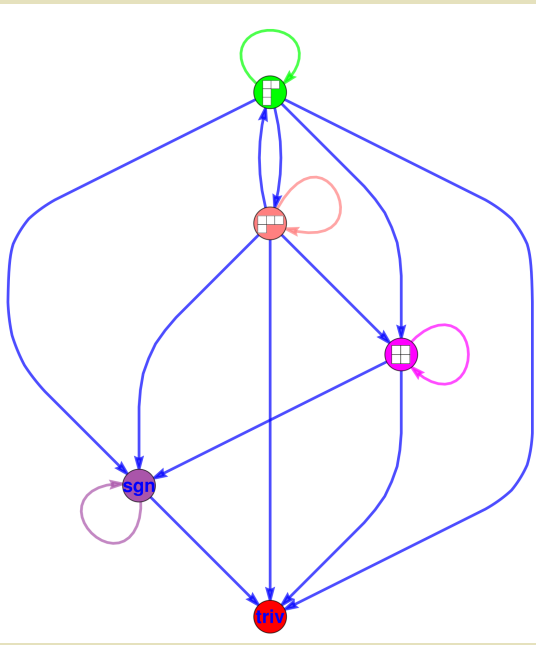
▶ Symmetric groups

▶ Products of these

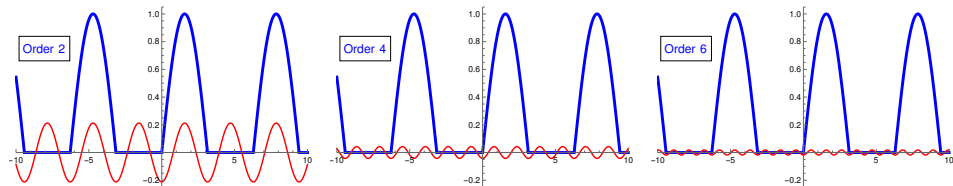
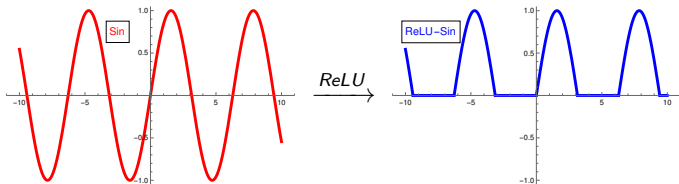
Γ for *ReLU* can thus
be considered as an invariant of the group C_n
or more generally for any finite group one gets an invariant

Let us study

Γ for the symmetric group S_4 (on isotypic components):

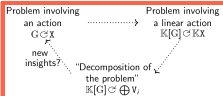


Let us study cyclic groups



- ▶ Linear map representation theory \leftrightarrow Fourier approximation of sin
- ▶ Piecewise linear map representation theory \leftrightarrow Fourier approximation of $ReLU \circ \sin$
- ▶ Higher frequencies \leftrightarrow simplices with a lot of ingoing arrows

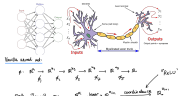
Learning with piecewise linear maps



- The **representation theory approach**: Decompose a problem into simple and take it from there
- **Today**: Representation theory and machine learning

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Learning with piecewise linear maps



- **Neural network**: "... a sequence of maps $\mathbb{R}^n \rightarrow \mathbb{R}^n \rightarrow \dots \rightarrow \mathbb{R}^m$
- **Deep** = many layers

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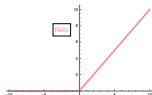
Learning with piecewise linear maps



- If our picture has some group symmetry then we should be able to use the **representation theory approach**, right?
- **Representation theory approach**

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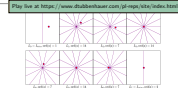
Learning with piecewise linear maps



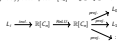
- **ReLU**: $\mathbb{R} \rightarrow \mathbb{R}, x \mapsto \max(x, 0)$ is the most popular activator map in machine learning
- Linear maps are **not** doing the job **Let us play fun**
- **Crucial 2**: Machine learning likes piecewise linear but non-linear maps

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Let us study cyclic groups

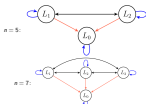


Thus, we can (explicitly) decompose $\mathbb{R}[C_n] \cong L_0 \oplus L_1 \oplus \dots$ and compute



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Let us study cyclic groups



- **Interaction graph**: vertices = simple, edges = nonzero maps $L_i \rightarrow L_j$
- This is a **measurement of difficulty**: a lot of ingoing arrows = hard

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Let us study cyclic groups

Calculation complexity is **captured in Γ**

Theorem
 $\#$ calls needed to evaluate f^* on L_i : number of length k paths winding at L_i in Γ_i .

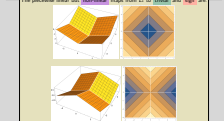
$\Gamma_{\text{ReLU}} =$

$\Gamma_{\text{ReLU} \circ \text{ReLU}} =$

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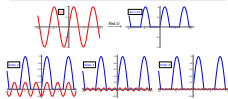
Let us study cyclic groups



Let us play online

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Let us study cyclic groups

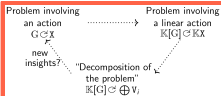


- Linear map representation theory **green**: Fourier approximation of \sin
- Piecewise linear map representation theory **red**: Fourier approximation of $\text{ReLU} \circ \sin$
- Higher frequencies **purple**: a lot of ingoing arrows

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There is still much to do...

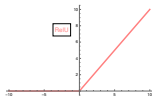
Learning with piecewise linear maps



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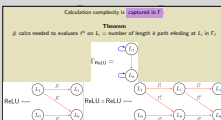
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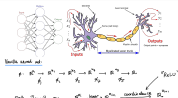
Let us study cyclic groups



- **Interaction graph Γ** : vertices = simplexes, edges = nonzero maps $L_i \rightarrow L_j$
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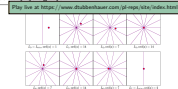
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Let us study cyclic groups

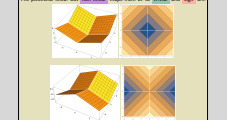


Thus, we can (explicitly) decompose $\text{ReLU} \cong L_0 \oplus L_1 \oplus \dots$ and compute

$$L_1 \xrightarrow{\text{ReLU}} \text{ReLU}[C] \xrightarrow{\text{ReLU}} \text{ReLU}[C] \xrightarrow{\text{ReLU}} L_2$$

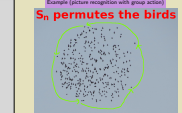
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Let



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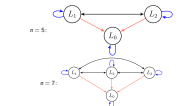
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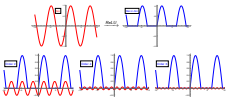
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Let us study cyclic groups



- Linear map representation theory **ReLU**: Fourier approximation of \sin
- Piecewise linear map representation theory **ReLU**: Fourier approximation of $\text{ReLU} \approx \sin$
- Higher frequencies = **simplexes** with a lot of ingoing arrows

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Thanks for your attention!