Equivariant Graph Neural Networks

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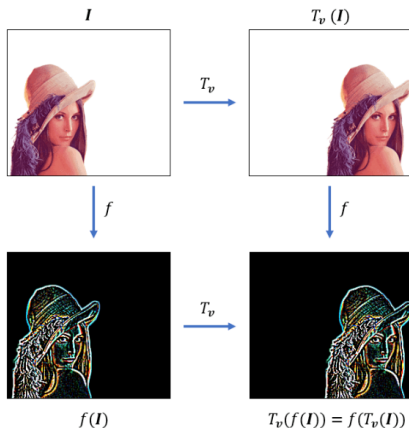December 26, 2024

Outline

1 Motivation

2 Mathematical Background

3 Deep Sets

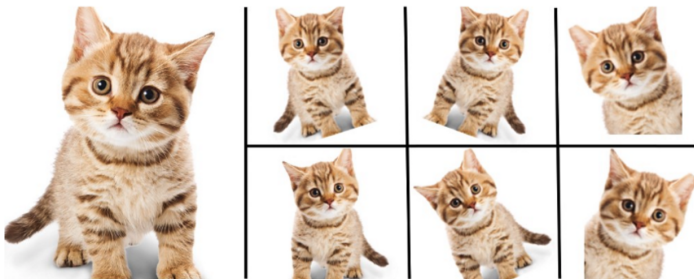4 Invariant and Equivariant Graph Networks

Motivation

- Our neural networks can operate on data of many types.
- We often work with images, text, audio, graphs and more.
- These data types have different structures and qualities, and we would like to build architectures that best suit them.
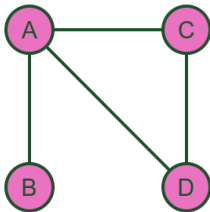
Motivation

- A cat is a cat no matter how you look at it.

- It is acceptable to assume that being invariant to the rotation of the cat is a good property for a classification network.
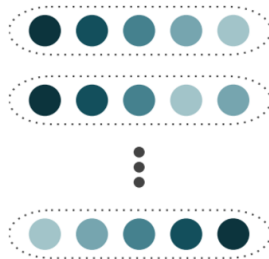
- Our focus today is on sets and graph data.

Simple graph

	A	B	C	D
A	0	1	1	1
B	1	0	0	0
C	1	0	0	1
D	1	0	1	0

Construction of an Equivariant Neural Network

- When contructing an equivariant neural network, two things should always be considered:
  1. The symmetries of the data:
     What inherent structure should our model be oblivious to?
  2. The space of functions learnable by the network:
     Are we fully utilizing the space of functions that are equivariant

The Permutation Group S_n

- The permutation group S_n is the group of all permutations of n elements.

- It has $n!$ elements, representing the $n!$ ways to order n elements.

- Given a set $X = \{x_1, x_2, \ldots, x_n\}$, a permutation $\pi \in S_n$ is a bijection $\pi : X \to X$

- e.g. $x = (x_1, x_2, x_3)$, and $\pi = (1, 2, 3) \in S_3$ is the permutation that maps $1 \to 2$, $2 \to 3$ and $3 \to 1$.

- We denote the **action** of π on x as $\pi x = (x_3, x_1, x_2)$.

Permutation Invariance

- Let $H \leq S_n$ be a subgroup of the symmetric group.

- $f : \mathbb{R}^n \to \mathbb{R}$ is *permutation invariant* if $f(x) = f(\pi x)$ for all $\pi \in H$.

$$f[\odot\odot\odot\odot] = \begin{bmatrix} 0.15 & 0.1 & 0.05 & \mathbf{0.8} \end{bmatrix}$$

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Permutation of a Set

- Assume our set is $X = \{x_1, x_2, \ldots, x_n\}$.

- We can represent X as a matrix $X \in \mathbb{R}^{n \times d}$.

- Any permutation $g \in S_n$ can be represented as a permutation matrix $\boldsymbol{P} \in \mathbb{R}^{n \times n}$,

- The action of g on X is then PX.

- An invariant neural network is a function $f : \mathbb{R}^{n \times d} \to \mathbb{R}^{d'}$ such that $f(X) = f(\boldsymbol{P}X)$.

- An equivariant neural network is a function $f : \mathbb{R}^{n \times d} \to \mathbb{R}^{n \times d'}$ such that $\boldsymbol{P}f(X) = f(\boldsymbol{P}X)$.

Permutation of a Graph

- Our data is now a graph adjacency matric $A \in \mathbb{R}^{n \times n}$.

- A permutation matrix $\boldsymbol{P} \in \mathbb{R}^{n \times n}$ acts on the adjacency matrix A.

- The action of $\boldsymbol{P}$ on A is:
$$\boldsymbol{P}^{\boldsymbol{T}} A \boldsymbol{P}$$

Equivariant Network Construction

Theorem

Let L be a linear equivariant layer, and let f be a neural network constructed be stacking L and non-linearities σ. Then f is permutation equivariant.

Proof.

Let x be a set of n elements, and let $g \in S_n$ be a permutation.

$$f(gx) = L(\sigma(L(\sigma(\dots L(gx)\dots)))) = L(\sigma(L(\dots g\sigma(L(x))\dots))) = \dots$$

$$gL(\sigma(L(\sigma(\dots L(x)\dots)))) = gf(x)$$

$\square$

Invariant Network Construction

Theorem

Let f be an equvariant neural network and let ϕ be a permutation invariant function. Then $h = \phi(f(x))$ is a permutation invariant neural network.

Proof.

Let x be a set of n elements, and let $g \in S_n$ be a permutation.

$$h(gx) = \phi(f(gx)) = \phi(gf(x)) = \phi(f(x)) = h(x)$$

$\square$

Deep Sets

- A seminal work in the field of equivariant neural networks.

- Recall the two properties we mentioned earlier (symmetries of the data and the space of functions learnable by the network).

- *DeepSets* is an architecture that is equivariant to set permutations and is maximmally expressive in the space of permutation equivariant functions.

- We are going to see the construction and prove it satisfies equivariance and expressiveness.

DeepSets Layer

- We saw a general structure of an invariant and equivariant network.

- To fill in the details, we need to define the equivariant layer L and the invariant function ϕ.

Definition

Consider a set $x = \{x_1, x_2, \ldots, x_n\}$, where $x_i \in \mathbb{R}$.
A *DeepSets* layer is defined as

$$L(x) = \lambda I \mathbf{x} + \mathbf{x1}$$

.

DeepSets Layer

Definition

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Theorem

A DeepSets layer is permutation equivariant.

Proof.

Let x be a set of n elements, and let $g \in S_n$ be a permutation.

$$L(gx) = \lambda I(gx) + (gx)\mathbf{1} = g(\lambda I x) + x\mathbf{1} = gL(x)$$

$\square$

DeepSets Network

- We have an initial layer L, which we proved is equivariant.

- A deep sets invariant network is now constructed as:

$$f(x) = \phi(L\sigma(L\sigma(\ldots L\sigma(L(x))\ldots))) \quad \text{where} \quad \phi(x) = \sum_{i=1}^{n} x_i$$

- It is easy to see that ϕ is permutation invariant, and thus f is permutation invariant.

- For a classification network, take some classification module ρ (e.g. an MLP), and define the final network as:

$$h(x) = \rho(f(x))$$

DeepSets Network

- Notice that the network is only defined for sets with elements in $\mathbb{R}$.

- We can extend this to a set $X \in \mathbb{R}^{n \times d}$ by defining L as:

$$L(x) = \mathbf{X}W_1 + \mathbf{1}\mathbf{1}^T\mathbf{X}W_2$$

- This keeps the general structure of the layer: a linear transformation of the distinct elements of the set summed with the mean of the set.

DeepSets Expressivity

- We have shown that the *DeepSets* network is permutation invariant.

- We now want to show that it is maximally expressive in the space of permutation invariant functions.

- We show outline for the proof, showing *DeepSets* can separate any two sets that are not equal.

Theorem

Let $x, y \in \mathbb{R}^{n \times d}$ s.t $x \neq gy$ $\forall g \in S_n$. Then there exists a DeepSets network that separates x and y, namely $F(x; \theta) \neq F(y; \theta)$.

DeepSets Expressivity

Proof outline:

1. Consider distinct rows of x, y.

2. Construct input output pairs using standard basis elements (one hot encodings of the elements in the set).

3. In each layer $L(x) = \mathbf{X}W_1 + \mathbf{1}\mathbf{1}^T\mathbf{X}W_2$, set $W_2 = 0$, collapsing our network to a standard MLP.

4. According to a result of the universal approximation theorem, we can learn a one to one mapping between the input and output pairs.

5. Output for each set the sum of the output pairs.

6. For each set, we computed the hitogram of its elements, which is a unique representation of the set.

Invariant and Equivariant Graph Networks

- We saw a simple, maximally expressive equivariant network for sets.

- We now want to extend this to graphs.

Invariant and Equivariant Graph Networks

- Recall the action of the permutation matrix $\boldsymbol{P}$ on the adjacency matrix A is:

$$\boldsymbol{P}^T A \boldsymbol{P}$$

- Lets use this to define a Linear invariant layer $L \in \mathbb{R}^{n \times n}$. We want to satisfy the following:

$$L\boldsymbol{P}^T A \boldsymbol{P} = L(A)$$

- But working with bilinear forms is hard. We can define an equivalent condition by column stacking the adjacency matrix to get a vector, and then define a linear layer $L \in \mathbb{R}^{1 \times n^2}$.

$$L\text{vec}(\boldsymbol{P}^T A \boldsymbol{P}) = L\text{vec}(A)$$

Invariant and Equivariant Graph Networks

- We now introduce a crucial property of the kronecker product:

$$\text{vec}(XAY) = Y^T \otimes X \text{vec}(A)$$

- Using this, the previous condition can be written as:

$$L(P^T \otimes P^T)\text{vec}(A) = L\text{vec}(A)$$

- For this condition to hold for all A, we need L to satisfy:

$$L(P^T \otimes P^T) = L$$

- transposing the equation, and with severe abuse of notation ($L^T = \text{vec}(L)$), we finally get:

$$(P \otimes P)\text{vec}(L) = \text{vec}(L)$$

Invariant and Equivariant Graph Networks

- After some work and moderate logic jumps, we got a condition for a permutation invariant linear layer L.

- Developing the condition for an equivariant layer is very similar:

$$L\text{vec}(\boldsymbol{P}^T A \boldsymbol{P}) = \boldsymbol{P}^T L\text{vec}(A)\boldsymbol{P}$$

- Using the kronecker product property, we get:

$$L(P^T \otimes P^T)\text{vec}(A) = (P^T \otimes P^T)L\text{vec}(A)$$

- This should hold for every A, so we get:

$$L(P^T \otimes P^T) = (P^T \otimes P^T)L$$

- $(P^T \otimes P^T)$ is an $n^2 \times n^2$ premutation matrix, and its inverse is $(P \otimes P)$.

$$(P^T \otimes P^T)L(P^T \otimes P^T) = L$$

- end

Thank You!