## Group Meeting - March 27, 2020

Paper review & Research progress

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# Greek philosophy & Stoicism (1)

#### Aristotle

A human is a **social creature**.





# Greek philosophy & Stoicism (2)

#### Marcus Aurelius

The happiness and unhappiness of the **rational**, **social animal** depends not on what he feels but on what he does just as his virtue and vice consist not in feeling but in doing.



# Greek philosophy & Stoicism (3)

#### Marcus Aurelius

Here is the rule to remember in future. When anything tempts you to be bitter: not, 'This is a misfortune' but 'To bear this worthily is good fortune.'.



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## Set2Graph (1)

#### Introduction

Many problems in machine learning can be cast as learning functions from sets to graphs, or more generally to hypergraphs; in short, **Set2Graph** functions. Current neural network models that approximate **Set2Graph** functions come from two main ML sub-fields:

- Equivariant learning
- Similarity learning



# Set2Graph (2)

#### **Problem**

Learning functions mapping sets of vectors in  $\mathbb{R}^{d_{in}}$  to graphs, or generally hypergraphs. For example:

- Clustering
- Predicting features on edges and nodes in graphs
- Learning k-edge information in sets

### Proposal

Model that can approximate arbitrary continuous **Set2Graph** functions over compact sets.



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## Set2Graph (3)

We represent each set-to-graph function as a collection of set-to-k-edge functions, where each set-to-k-edge function learns features on k-edges.

Given an input set  $\mathcal{X} = \{x_1, ..., x_n\} \subset \mathbb{R}^{d_{in}}$ , we consider functions  $F^k$  attaching feature vectors to k-edges: each k-tuple  $(x_{i_1}, ..., x_{i_k})$  is assigned with an output vector  $F^k(\mathcal{X})_{i_1, i_2, ..., i_k} \in \mathbb{R}^{d_{out}}$ .

Functions mapping sets to hypergraphs with hyper-edges of size up-to-k are modeled by  $(F^1, F^2, ..., F^k)$ . Functions mapping set to standard graphs are represented by  $(F^1, F^2)$ . Set-to-graph functions are well-defined if satisfy a property called **equivariance**.

# Set2Graph (4)

#### (Maron et al., 2019) - Invariant and Equivariant Graph Networks

- Full equivariant model.
- Each linear layer is chosen from the space of all linear equivariant layers.
- Learning F<sup>k</sup> would require equivariant layers mapping 1st-order tensor (representing sets) to k-order tensors (representing k-edge hypergraphs).
- Omputationally infeasible ← I think it is similar to CCNs (out of PSPACE)!



# Set2Graph (5)

#### Theoretical question - Universality

- Universality is the ability of the models to approximate any continuous equivariant function.
- Set-to-Set models: universal.
- Graph-to-Graph models (message passing): non-universal.
- High-order equivariant models: universal.

Another machine-learning approach for learning set-to-graph functions is similarity learning: A siamese network  $\phi$  is used to embed each set element independently  $y_i = \phi(x_i)$  and pairwise information is extracted from pairs of embeddings  $\psi(y_i, y_i)$ .

# Set2Graph (6)

#### Proposal

Composition of three networks:

$$F^k = \psi \circ \beta \circ \phi$$

- $\phi$ : Set-to-Set model.
- $\beta$ : Non-learnable broadcasting Set-to-Graph layer.
- $\psi$ : Simple Graph-to-Graph network using only a single MLP acting on each k-edge feature vector independently.



## Set2Graph (7)

A matrix  $X = (x_1, ..., x_n)^T \in \mathbb{R}^{n \times d_{in}}$  represents a set of n vectors  $x_i \in \mathbb{R}^{d_{in}}$ . Reordering the rows of X by the permutation  $\sigma$ :

$$(\sigma \cdot X)_{i,j} = X_{\sigma^{-1}(i),j}$$

X and  $\sigma \cdot X$  represent the same set for all  $\sigma \in \mathbb{S}_n$ .

A tensor  $Y \in \mathbb{R}^{n^k \times d_{out}}$  where  $Y_{i,:} \in \mathbb{R}^{d_{out}}$  represents the feature vector attached to the k-edge defined by the k-tuple  $(x_{i_1},..,x_{i_k})$ , where  $i=(i_1,..,i_k)\in [n]^k$  without repeating indices:

$$(\sigma \cdot Y)_{i,j} = Y_{\sigma^{-1}(i),j}$$

$$\sigma^{-1}(i) = (\sigma^{-1}(i_1), ..., \sigma^{-1}(i_k))$$

Y and  $\sigma \cdot Y$  represent the same k-edge data for all  $\sigma \in \mathbb{S}_n$ .



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# Set2Graph (8)

### Equivariance

For  $F^k$  to represent a well-defined map between sets  $X \in \mathbb{R}^{n \times d_{in}}$  and k-edge data  $Y \in \mathbb{R}^{n^k \times d_{out}}$ , it should be equivariant to permutations:

$$F^k(\sigma \cdot X) = \sigma \cdot F^k(X)$$

#### Theorem 1

The model  $F^k$  is set-to-k-edge universal.

#### Theorem 2

The model  $(F^1, ..., F^k)$  is set-to-hypergraph universal.



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## Set2Graph (10)

- Partitioning for particle physics
- Learning Delaunay triangulations
- Molecular properties prediction
- 3D convex hull



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# Set2Graph & CCNs in solving NP-complete & NP-hard problems

#### NP-hard

Finding the minimum Hamiltonian cycle/path given a set of points is a **Set2Graph** problem.

#### NP-complete

Can Set2Graph and CCNs estimate/approximate the solution of NP-complete problems (e.g. 3-SAT, Hamiltonian)?

