

A Neural Framework for Learning DAG to DAG Translation

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Problem

Learn function mappings that translate a DAG to another DAG while preserving syntactic and semantic similarities, applications in e.g. query optimization, circuit simplification, code translation, etc.

Our Solution

DAG-to-DAG Recursive Neural Network (D2DRNN):

A novel neural encoder-decoder framework for learning functions from a graph space onto another graph space - aka DAG-to-DAG translation. Full paper: https://claradepaolis.github.io/D2DRNN/

DAG-to-DAG RNN model

We generalize the **Seq2Seq** architecture to the graph space where the input DAGs are mapped into a real vector space via a graph encoder and the output graphs are

Logical Circuit Simplification

Given an input logical circuit, the goal is to output an *equivalent* and *syntacticallycorrect* circuit with smaller number of gates.



Each circuit is represented as a DAG where nodes represent the variables and gates and the node feature vectors encode the gate type.

Experiments



synthesized from the same vector space into DAGs via a graph decoder.



Model overview

Graph Encoder: Analyzing Input Graph Deep-Gated DAG Recursive Neural Network (DG-DAGRNN)[1]



$$\boldsymbol{h}_{v} = GRU(\boldsymbol{x}_{v}, \boldsymbol{h}_{v}'), \text{ where } \boldsymbol{h}_{v}' = \mathcal{A}\left(\{\boldsymbol{h}_{u}|u \in \pi(v)\}\right)$$

Graph Decoder: Synthesizing Output Graph



Baselines

Seq2Seq[2]: DAGS as sequences of nodes Seq2DAG: sequence of nodes to DAG decoder **DAG2Seq**: DAG encoder to sequence decoder **Errors** (lower is better):





Valid Syntax (higher is better):





Supervised Loss Function: $\mathcal{L} = \mathcal{L}_{length} + \mathcal{L}_{nodes} + \mathcal{L}_{structure}$ $\mathcal{L}_{length} = \text{Poisson-NLL-Loss}(f_{Length}(\boldsymbol{H}_{in}), |V_{target}|) \approx |V_{out}| - |V_{target}|\log(|V_{out}|)$ $\mathcal{L}_{nodes} = \text{Cross-Entropy}(V_{out}, V_{target})$ $\mathcal{L}_{structure} = \text{Diffusion}(\mathbf{A}_{out}, \mathbf{A}_{target}) = \text{MSE}(\mathbf{A}_{out}\mathbf{r}, \mathbf{A}_{target}\mathbf{r})$

Open Problems

- Supervised Learning is not always the best approach to address graph-to-graph translation, especially when labeled data is not available or the desired output DAGs are not unique.
- Unlike syntactical constraints, enforcing semantic constraints is very challenging in the encoder-decoder design.

References

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 - In Advances in neural information processing systems, pages 3104–3112, 2014.