Neural Inference of API Functions from Input–Output Examples

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Introduction

- Discovering what APIs to use can be time difficult and time-consuming
- Speed of creation of new APIs outpaces the completeness, clarity, and even correctness of the documentation
- **Program synthesis** is the process of automatically generating a program conforming to a higher-level specification
- Goal is the automating the process of finding the correct API given a set of input-output values

Challenges

- For a language with **n functions**, taking an average of **m argument** values, the **number of sequential programs** of **length k** grows as $\mathbf{(nm)^k}$
- Existing approaches work on small subsets of problems or Domain Specific Languages
- Identify the actual function and its arguments, which may have interactions
- Exhaustive search is feasible for determining arguments but not functions
- Use a hybrid approach with exhaustive search for arguments and a neural inference mechanism to predict the functions

Methodology

Map a given I/O example to a pandas function which performs the transformation specified by the example

Steps:

1. Preprocessing I/O examples into a graph
2. Feeding these examples into a trainable neural network which learns a high-dimensional representation for each node of the graph,
3. Pooling to output of the neural network and applying softmax to select a pandas function.
4. Use exhaustive search to find the correct arguments

Graph Abstraction

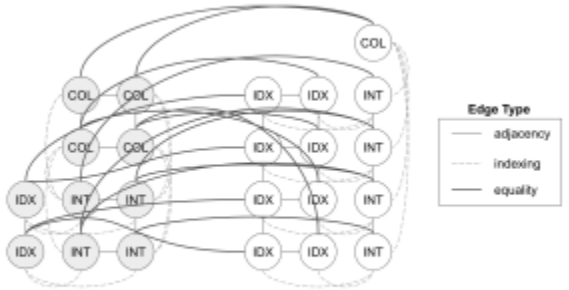
The operation used in an I/O example is often captured by the relationships amongst the elements, rather than the concrete data itself

	weight	
	kg	lbs
cat	1	2
dog	2	4

input

		weight
cat	kg	1
	lbs	2
dog	kg	2
	lbs	4

output



(a) DataFrame I/O Example. White cells are data; pale gray are row indices, and dark grey are column names.

(b) Graph Representation. Gray nodes come from the input DataFrame, white nodes from the output.

Nodes

- Every data cell in the input and output DataFrame is represented as a single node
- Multiple levels of column names or row indices appear as additional nodes
- Node is labeled with a **type tuple (data type, is input)**

Edges

- Edges to represent the relationships between nodes in input and output
- **Equality edges** are between any nodes with the same value
- **Adjacency edges** represent the basic structural characteristics of the DataFrames
- **Indexing edges** are between a column name (resp. row index) and all the data nodes that belong to that column

Gated Graph Neural Networks

Graph Neural Networks map graphs to outputs via two steps:

1. **Propagation** step that computes node representations for each node
2. Compute **output model** that maps from node representations and corresponding labels to an output

Gated Graph Neural Networks: GNN with recurrent unit that stores node state and uses backpropagation through time in order to compute gradient

Network

- **Edge e** is a **3-tuple (v_s, v_t, t_e)** where v_s and v_t are the source and target nodes and t_e is the type of the edge.
- Every node v has a corresponding **state vector**
- Information is propagated using **message passing** across k rounds
- For each node, the **incoming messages** are **aggregated**
- The new node state vector for the next round is computed using **recurrent unit**
- **Element-wise sum-pool** the node state vectors into a graph state vector h.
- Use a multi-layer perceptron with one hidden layer, and apply softmax to produce a probability distribution over the target classes

Accuracy Results

Accuracy is computed using (1) synthesized validation set and (2) I/O examples taken from real-world sources

Table 1: Accuracy in predicting the ground-truth or a correct function for I/O examples.

	Ground-Truth		**Success Rate**	
	Top-1	*Top-5*	*Top-1*	*Top-5*
Validation	65%	94%	82%	97%
Test	59%	83%	69%	83%
Clean Test	66%	97%	83%	97%

Table 2: Effect of graph abstraction features on Top-1 validation accuracy.

Control	**Acc.**
No Node Features	57%
No Edge Features	63%
No Structural Edges	61%
No Equality Edges	46%

Thoughts

Pros:

- Encoding I/O pairs as a graph
- Flexible compared to existing approaches

Doubts:

- Limited to single function programs
- Scalability and performance in real world data
- Does not consider parameter selection