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APPLIED RESEARCH IN ACTION

Abstract Syntax Tree Coarsening via Deep Attention-Based Node Pooling Auto-Encoders

Attention-based graph coarsening allows for significant reduction of the size of graphs, while retaining sufficient information for graph reconstruction, as well as downstream classification tasks versus traditional algorithmic coarsening methods.

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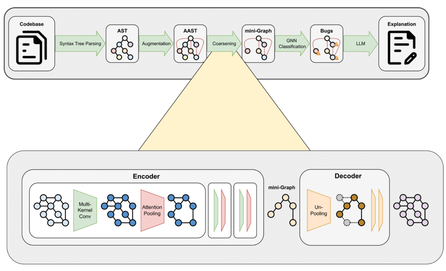

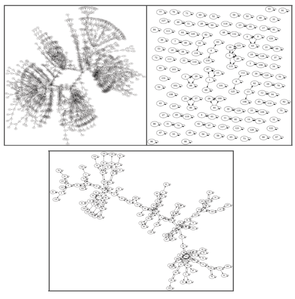

PROJECT SUMMARY

Files of code, and collections of files (codebases), can be easily converted to an abstract syntax tree (AST) representation that contains sufficient semantic/structural information to run a program. These tree structures lend themselves naturally to be used in graph neural networks (GNNs) for static analysis of code files and codebases. However, both ASTs and GNNs are memory intensive, in that the former can be quite large and the latter do not scale well with large inputs. To solve this compatibility issue between the two, previous approaches have used heuristics to coarsen ASTs, thereby reducing their size before passing them to GNNs. These approaches suffer in their inability to rely on data to learn how to best coarsen a graph to retain information. In this work, we propose ASTA Encoder (AST Attention Encoder), a data-driven approach to learn how to condense ASTs, with the goal of passing them to a downstream GNN task. This approach introduces novelty to the graph auto-encoder architecture by calculating a learnable node importance score that incorporates edge directionality, which allows the network to understand the effect of dropping nodes with certain parent/child relationships. We train an attention-based GNN auto-encoder network on thousands of ASTs coming from a custom augmented AST parser used on public Python GitHub repositories. We show that graphs can be reduced in size by 92.5% while still increasing performance on downstream graph classification tasks.

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