A Common Graph Representation for Source Code and Developer Documentation

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Abstract

Semantic information plays a key role in the code search and synthesis settings. In this work, we propose a graph-based representation for source code and natural language which incorporates semantic and relational features from both domains. We apply this graph to a parsing a corpus of code and developer documents, and demonstrate the effectiveness of a common graph-based representation on three downstream tasks: code search, document recommendation and link prediction.

1 Background and motivation

In addition to its syntactic structure, source code contains a rich denotational and operational semantics [Henkel et al., 2018]. To effectively reason about code in semantically similar but syntactically diverse settings requires models which incorporate features from the call graph [Gu et al., 2016, Liu et al., 2019] and surrounding typing context [Allamanis et al., 2017]. Many semantic features, such as data and control flow [Si et al., 2018] can be represented as a directed acyclic graph (DAG), which admits linear-time solutions to a number of graph problems, including topological sorting, single-source shortest path and reachability queries.

DAGs also have important applications in natural language parsing [Sagae and Tsujii, 2008, Quernheim and Knight, 2012]. Various attempts to build semantic representations for natural language have been proposed, notably the pointer network architecture [Vinyals et al., 2015b,a]. Pointer networks help to capture permutation-invariant semantic relations between natural language entities, and have important applications in dependency parsing [Ma et al., 2018], named-entity recognition [Lample et al., 2016], and other tasks where sequence representations fall short. Li et al. [2017] extend pointer networks with a copy-mechanism to handle out-of-vocabulary code tokens.

Content recommendation for doc-to-doc (D2D) and code-to-code (C2C) is a relatively straightforward application of existing link prediction [Zhang and Chen, 2018] and code embedding [Gu et al., 2018] techniques, but cross-domain transfer remains largely unsolved. Robillard and Chhetri [2015], Robillard et al. [2017] first explore the task of predicting reference API documentation from source code using manual annotation. Prior work also studies the association between comments and code entities [Panthaplackel et al., 2020] using machine learning, but only within source code.

Maintainers of widely-used software projects often publish web-based documentation, typically stored in markup languages like HTML or Markdown. These files contain a collection of natural language sentences, markup, and hyperlinks to other documents. Both the link graph and the document tree contain important semantic information: the markup describes the text in relation to the other entities in the document hierarchy [Yang et al., 2016], while the link graph describes the relationship between the parent document and related documents or source code entities. Documents occasionally contain hyperlinks to source code, but source code rarely contains links to developer documents.

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Some programming languages allow users to specify which type of values will inhabit a given variable at runtime. Types allow the compiler to reason about certain properties like nullity [Ekman and Hedin, 2007] and shape [Considine et al., 2019]. While types many not appear explicitly in source code, they can often be inferred from the surrounding context using a dataflow graph (DFG). The Java language recently introduced local variable type inference Liddell and Kim [2019], which allows variable types to be omitted, and later inferred by the compiler.

2 Proposed approach

Given a single token in either source code or developer documentation and its surrounding context, what are the most relevant source code or documentation entities related to the token in question? We would like to infer which entities are relevant to a particular token, based on the semantic context. To infer links across these two domains requires building a multi-relational graph, using features extracted from both natural language and source code. Following Si et al. [2018], Gu et al. [2018], Liu et al. [2019], we use a node embedding on the dataflow graph and type environment, and following Yang et al. [2016], Zhang and Chen [2018], use the markup hierarchy and link graph to construct an embedding for code-like tokens used within documentation.

To compensate for the sparsity of hyperlinks between code and documentation, we must design a heuristic to connect the documentation graph and source code entities. One heuristic which developers often use to discover relevant documents is plaintext search on a salient lexical string. Co-occurrence of an infrequent token indicates the two entities are likely related, even though they may not share an explicit grammatical link. If we can recover this relationship without observing the lexical token itself, only using dataflow and type-related information, this indicates our representation is providing useful information.

3 Data availability and computational requirements

Java, one of the most popular programming languages on GitHub, is a statically typed language with an extensive amount of API documentation on the web. It has a variety of tools for parsing and analyzing both code [Kovalenko et al., 2019] and natural language [Manning et al., 2014, Grella and Cangialosi, 2018], making it a suitable candidate both as a dataset and implementation language. Our dataset consists of Java repositories on GitHub, and their accompanying docs on the Zeal software documentation aggregator. All projects in our dataset have a collection of source code files and multiple related repositories on GitHub.

We construct two datasets consisting of naturally-occurring links between developer documentation and source code, and a surrogate set of links constructed by matching lexical tokens available in both domains. Our target is the recovery of ground truth links in our test set and surrogate links in the lexical matching graph. By adding weighted edges between source code and documentation and learning the relations using, e.g. a pointer network architecture, we evaluate our approach on reconstructing synthetic links between tokens contained in code-like fragments and markup entities which refer to the selected token. In addition, we evaluate our approach both on D2D and C2C link retrieval, as well as precision and recall on the surrogate link graph.

To perform our experiments, we require a large number of CPUs for semantic parsing, link extraction and graph preprocessing, and a single P100 GPU for training a graph neural network. We have applied and received access to the Niagra CC cluster.

References

Miltiadis Allamanis, Marc Brockschmidt, and Mahmoud Khademi. Learning to represent programs with graphs. *arXiv preprint arXiv:1711.00740*, 2017. URL `https://arxiv.org/pdf/1711.00740.pdf`.

Breandan Considine, Michalis Famelis, and Liam Paull. Kotlin∇: A shape-safe eDSL for differentiable programming. `https://github.com/breandan/kotlingrad`, 2019.

Torbjörn Ekman and Görel Hedin. Pluggable checking and inferencing of nonnull types for Java. *Journal of Object Technology*, 6(9):455–475, 2007. URL http://www.jot.fm/issues/issue_2007_10/paper23.pdf.

Matteo Grella and Simone Cangialosi. Non-projective dependency parsing via latent heads representation LHR. *arXiv preprint arXiv:1802.02116*, 2018. URL https://arxiv.org/pdf/1802.02116.pdf.

Xiaodong Gu, Hongyu Zhang, Dongmei Zhang, and Sunghun Kim. Deep API learning. In *Proceedings of the 2016 24th ACM SIGSOFT International Symposium on Foundations of Software Engineering*, pages 631–642, 2016. URL https://arxiv.org/pdf/1605.08535.pdf.

Xiaodong Gu, Hongyu Zhang, and Sunghun Kim. Deep code search. In *2018 IEEE/ACM 40th International Conference on Software Engineering (ICSE)*, pages 933–944. IEEE, 2018. URL https://guxd.github.io/papers/deepcs.pdf.

Jordan Henkel, Shuvendu K Lahiri, Ben Liblit, and Thomas Reps. Code vectors: Understanding programs through embedded abstracted symbolic traces. In *Proceedings of the 2018 26th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering*, pages 163–174, 2018. URL https://arxiv.org/pdf/1803.06686.pdf.

Vladimir Kovalenko, Egor Bogomolov, Timofey Bryksin, and Alberto Bacchelli. PathMiner: a library for mining of path-based representations of code. In *Proceedings of the 16th International Conference on Mining Software Repositories*, pages 13–17. IEEE Press, 2019. URL https://github.com/JetBrains-Research/astminer.

Guillaume Lample, Miguel Ballesteros, Sandeep Subramanian, Kazuya Kawakami, and Chris Dyer. Neural architectures for named entity recognition. *arXiv preprint arXiv:1603.01360*, 2016. URL https://arxiv.org/pdf/1603.01360.pdf.

Jian Li, Yue Wang, Michael R Lyu, and Irwin King. Code completion with neural attention and pointer networks. *arXiv preprint arXiv:1711.09573*, 2017. URL https://www.ijcai.org/Proceedings/2018/0578.pdf.

Clayton Liddell and Donghoon Kim. Analyzing the adoption rate of local variable type inference in open-source Java 10 projects. *Journal of the Arkansas Academy of Science*, 73(1): 51–54, 2019. URL https://scholarworks.uark.edu/cgi/viewcontent.cgi?article=3346&context=jaas.

Bohong Liu, Tao Wang, Xunhui Zhang, Qiang Fan, Gang Yin, and Jinsheng Deng. A neural-network based code summarization approach by using source code and its call dependencies. In *Proceedings of the 11th Asia-Pacific Symposium on Internetware*, Internetware '19, New York, NY, USA, 2019. Association for Computing Machinery. ISBN 9781450377010. doi: 10.1145/3361242.3362774. URL https://doi.org/10.1145/3361242.3362774.

Xuezhe Ma, Zecong Hu, Jingzhou Liu, Nanyun Peng, Graham Neubig, and Eduard Hovy. Stack-pointer networks for dependency parsing. *arXiv preprint arXiv:1805.01087*, 2018. URL https://arxiv.org/pdf/1805.01087.pdf.

Christopher D Manning, Mihai Surdeanu, John Bauer, Jenny Rose Finkel, Steven Bethard, and David McClosky. The stanford coreNLP natural language processing toolkit. In *Proceedings of 52nd annual meeting of the association for computational linguistics: system demonstrations*, pages 55–60, 2014. URL https://nlp.stanford.edu/pubs/StanfordCoreNlp2014.pdf.

Sheena Panthaplackel, Milos Gligoric, Raymond J. Mooney, and Junyi Jessy Li. Associating natural language comment and source code entities. In *AAAI*, 2020. URL https://arxiv.org/pdf/1912.06728.pdf.

Daniel Quernheim and Kevin Knight. Dagger: A toolkit for automata on directed acyclic graphs. In *Proceedings of the 10th International Workshop on Finite State Methods and Natural Language Processing*, pages 40–44, 2012. URL https://www.aclweb.org/anthology/W12-6207.pdf.

Martin P Robillard and Yam B Chhetri. Recommending reference API documentation. *Empirical Software Engineering*, 20(6):1558–1586, 2015. URL https://www.cs.mcgill.ca/~martin/papers/cr2014a.pdf.

Martin P Robillard, Andrian Marcus, Christoph Treude, Gabriele Bavota, Oscar Chaparro, Neil Ernst, Marco Aurélio Gerosa, Michael Godfrey, Michele Lanza, Mario Linares-Vásquez, et al. On-demand developer documentation. In *2017 IEEE International Conference on Software Maintenance and Evolution (ICSME)*, pages 479–483. IEEE, 2017.

Kenji Sagae and Jun'ichi Tsujii. Shift-reduce dependency DAG parsing. In *Proceedings of the 22nd International Conference on Computational Linguistics-Volume 1*, pages 753–760. Association for Computational Linguistics, 2008. URL https://www.aclweb.org/anthology/C08-1095.pdf.

Xujie Si, Hanjun Dai, Mukund Raghothaman, Mayur Naik, and Le Song. Learning loop invariants for program verification. In *Advances in Neural Information Processing Systems*, pages 7751–7762, 2018. URL https://papers.nips.cc/paper/8001-learning-loop-invariants-for-program-verification.pdf.

Oriol Vinyals, Samy Bengio, and Manjunath Kudlur. Order matters: Sequence to sequence for sets. *arXiv preprint arXiv:1511.06391*, 2015a. URL https://arxiv.org/pdf/1511.06391.pdf.

Oriol Vinyals, Meire Fortunato, and Navdeep Jaitly. Pointer networks. In *Advances in neural information processing systems*, pages 2692–2700, 2015b. URL https://arxiv.org/pdf/1506.03134.pdf.

Zichao Yang, Diyi Yang, Chris Dyer, Xiaodong He, Alex Smola, and Eduard Hovy. Hierarchical attention networks for document classification. In *Proceedings of the 2016 conference of the North American chapter of the association for computational linguistics: human language technologies*, pages 1480–1489, 2016. URL https://www.cs.cmu.edu/~./hovy/papers/16HLT-hierarchical-attention-networks.pdf.

Muhan Zhang and Yixin Chen. Link prediction based on graph neural networks. In *Advances in Neural Information Processing Systems*, pages 5165–5175, 2018. URL https://papers.nips.cc/paper/7763-link-prediction-based-on-graph-neural-networks.pdf.