```
pgf@stop
```

Learning to Search for Code

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Abstract

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

1 Introduction

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.

Natural language also contains semantic information which can be represented using graphs. The NLP community has a rich set of graph-based representations, including Reddy et al. [2016]'s and other typed attribute grammars which can be used to reason about syntactic and semantic relations. The pointer network architecture [Vinyals et al., 2015b,a] can be used to construct permutation-invariant semantic relations between natural language entities, and has important applications in dependency parsing [Ma et al., 2018], named-entity recognition [Lample et al., 2016], and other semantic parsing tasks where sequence-based 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) can be solved with existing link prediction [Zhang and Chen, 2018] and code embedding [Gu et al., 2018] techniques, but cross-domain transfer remains challenging. Robillard and Chhetri [2015], Robillard et al. [2017] first explore the task of predicting reference API docs from source code using manual annotation. Prior work also studies the association between comments and code entities [**??**] using machine learning, but only within source code.

Maintainers of widely-used software projects often publish web-based developer docs, 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 docu-

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ments or source code entities. Documents occasionally contain hyperlinks to source code, but source code rarely contains links to developer documents.

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). For example, 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.

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? We would like to infer which entities are related to a given token, based on the surrounding context. Learning relationships between these two domains usually requires langauge-specific parsers. Prior work has explored incorporating dataflow and type information Si et al. [2018], Gu et al. [2018], Liu et al. [2019], as well as the markup language and link graphYang et al. [2016], Zhang and Chen [2018] to construct an embedding for code-like tokens used within documentation.

When linking from code to documentation, or documentation to code, the sparsity of cross-domain links presents a significant challenge. To compensate for the sparsity of hyperlinks between code and documentation, we require a mapping between the documentation graph and source code entities. One heuristic which developers often use to discover relevant documents is text search. These tokens are often written in a domain specific language (DSL), either explicitly or implicitly takes the form of a regular expression (regex), which most search engines are capable of recognizing. Skilled users are able to rapidly construct a sequence of search tokens which retrieve the document with high probability while omitting irrelevant results.

Unlike natural language where entities are often ambiguous strings, source code often has a canonical representation which unambiguously identifies the entity in question. In most cases, entity linking in this setting consists of a simple set of pattern matching rules, which a skilled developer can recognize. Given a string, `AbstractSingletonProxyFactoryBean`, we observe it has the following properties:

1. The string is camelcase, indicating it refers to an entity in a camel-case language.
2. The string contains the substring `Bean`, a common token in the Java language.
3. The string begins with a capital letter, indicating it refers to a `class`.

To locate the entity in question we can simply execute the following command on a shell:

```
$ grep -r --include .java "class AbstractSingletonProxyFactoryBean" .
```

For most programming languages, most API entities are unambiguously named. We hypothesize there is a short query which uniquely identifies the canonical entity and furthermore, it is possible to learn a program which synthesizes a query that retrieves this entity in a data-driven manner.

2 Background

Let $\Sigma = \{$`A`, `a`, ..., `Z`, `z`, `0`, `1`, ..., `9`, `$`, `^`$\}$. Our language $J_<$ has the following productions:

$$\langle exp \rangle ::= \langle exp \rangle \langle exp \rangle \;\mid\; \langle exp \rangle | \langle exp \rangle \;\mid\; \texttt{(} \langle exp \rangle \texttt{)} \;\mid\; \alpha \in \Sigma \;\mid\; \langle exp \rangle \texttt{*} \;\mid\; \texttt{.} \tag{1}$$

An expression in this language corresponds to a regular expression, reducible to a non-deterministic finite automata (NFA) using Glushkov's algorithm [Glushkov, 1961], as shown in Figure 1. NFA are also reducible to both deterministic finite automata (DFA) using the powerset construction [Rabin and Scott, 1959] and regular expressions using Arden's Lemma [Arden, 1961].

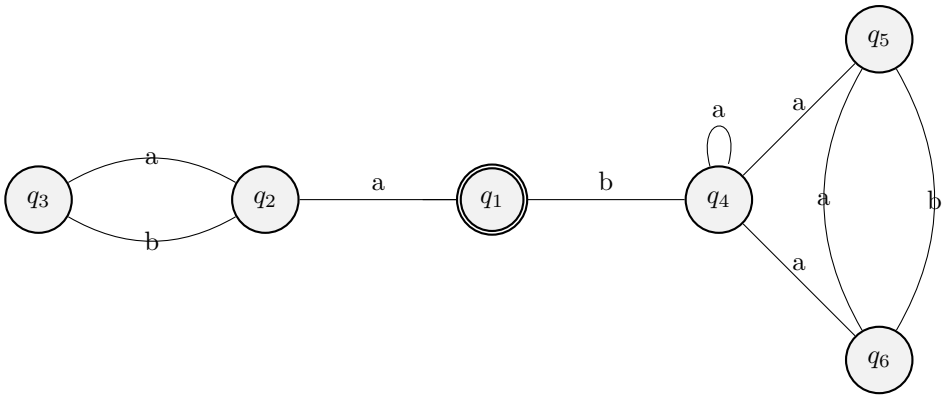


Figure 1: NFA corresponding to the regular expression `(a(ab)*)*(ba)*`.

Formally, an NFA is a 5-tuple $(Q, \Sigma, \Delta, q_0, F)$, where Q is a finite set of states, Σ is the alphabet, $\Delta : Q \times (\Sigma \cup \{\epsilon\}) \to P(Q)$ is the transition function, $q_0 \in Q$ is the initial state and $F \subseteq Q$ are the terminal states. An NFA can be represented by a directed graph whose adjacency matrix is defined by the transition function, with edge labels representing symbols from the alphabet and binary node labels indicating whether the node is a terminal or nonterminal state.

We pose the problem as a few-shot generative modeling task, where the input is a local graph consisting of the query text, and the output is an adjacency matrix defining the NFA. Our goal is to synthesize an NFA which accepts the target document and no other documents or as few others as possible from the entire corpus.

3 Method

Let $\mathcal{T}$ be a code token, corresponding to a node in a document graph $\mathcal{D}$, representing a semantic parse of the document's contents, and neighboring documents from the link graph. We train a meta learner $\mathcal{M}$ on the following objective:

$$\mathbb{E}_{L \subset \mathcal{L}}[\mathbb{E}_{S^L \subset \mathcal{D}, B^L \subset \mathcal{D}}[\sum_{(\mathbf{x}, y) \in B^L} \mathcal{M}_{g_\phi(\theta, S^L)}(y|\mathbf{x})]] \tag{2}$$

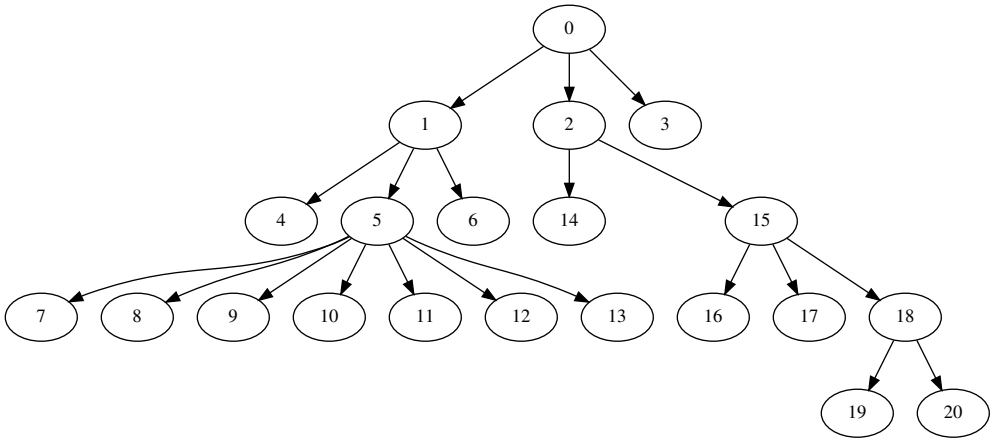
4 Data availability

Java, one of the most prolific programming languages on GitHub, is a statically typed language with a high volume of API documentation. Offering a variety of tools for source code [Parr, 2013, Hosseini and Brusilovsky, 2013, Kovalenko et al., 2019] and natural language [Manning et al., 2014, Grella and Cangialosi, 2018] parsing, it is a convenient language for both analysis and implementation. Our dataset consists of Java repositories on GitHub, and their accompanying developer documents. 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 docs and source code, and a surrogate set of links constructed by matching lexical tokens available in both domains. Our target is recovery of ground truth links in the test set and surrogate links in the lexical matching graph. We first add weighted edges between code and docs, then evaluate our approach by predicting synthetic links between tokens contained in code fragments and markup entities which refer to the selected token. In addition, we evaluate our approach on both D2D and C2C link retrieval, as well as precision and recall on the surrogate link relations.

Our data consists of two complementary datasets: abstract syntax trees collected from Java source code and developer documentation. We use the astminer [Kovalenko et al.,

2019] library to parse Java code, jsoup [Hedley, 2009] to parse HTML and Stanford's CoreNLP [Manning et al., 2014] library to parse dependency graphs from developer docs. Consider the following AST, parsed from the Eclipse Collections Java project:



The AST depicted above was generated by parsing the following code snippet:

```
public void lastKey_throws() {
    new ImmutableTreeMap<>(new TreeSortedMap<>()).lastKey();
}
```

Now consider the following dependency graph, taken from a Javadoc in the same project:

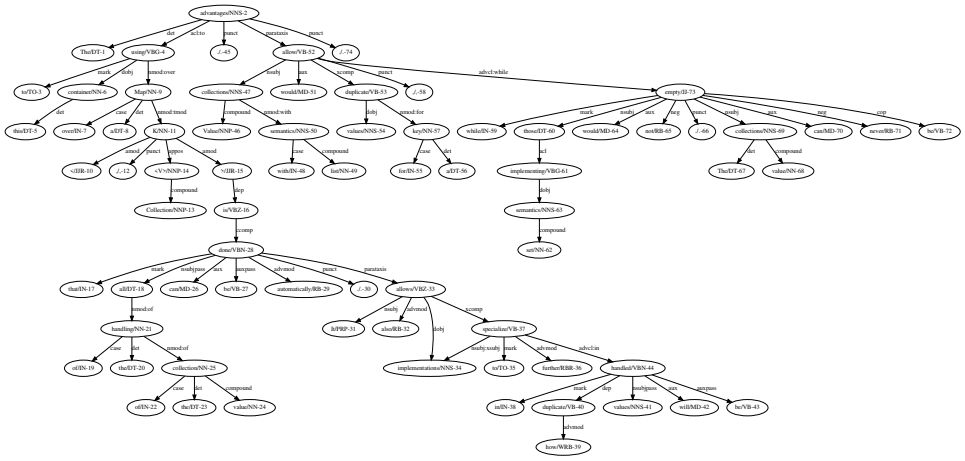


Figure 2: This graph was parsed from the following comment: "The advantages to using this container over a `Map<K, Collection<V>>` is that all of the handling of the value collection can be done automatically. It also allows implementations to further specialize in how duplicate values will be handled. Value collections with list semantics would allow duplicate values for a key, while those implementing set semantics would not. The value collections can never be empty."

Our goal is to connect these two graphs using a common model for source code and natural language. Absent any explicit `@link` or `@see` annotations, in order to relate these two graphs, we must somehow infer the shared semantic entities, which we can do for a subset using a simple lexical matching procedure.

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