Analyzing Software using Deep Learning

Token Vocabulary and Code Embeddings (Part 1)

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Overview

- **Token vocabulary problem**
- **Pre-trained token embeddings**
- **Joint embedding space for NL & PL**

Recommended papers:

- ”Distributed representations of words and phrases and their compositionality”, NIPS, 2013
- ”Big Code != Big Vocabulary - Open-Vocabulary Models for Source Code”, ICSE, 2020
- ”Deep Code Search”, ICSE, 2018

Tokens: Building Blocks of Code

- Source code = Sequence of tokens
- Reasoning about large code snippets: Need to reason about tokens first

```
// From Angular.js
browserSingleton.startPoller(100,
    function(delay, fn) {
        setTimeout(delay, fn);
    });
```

Kinds of Tokens

Two categories of tokens

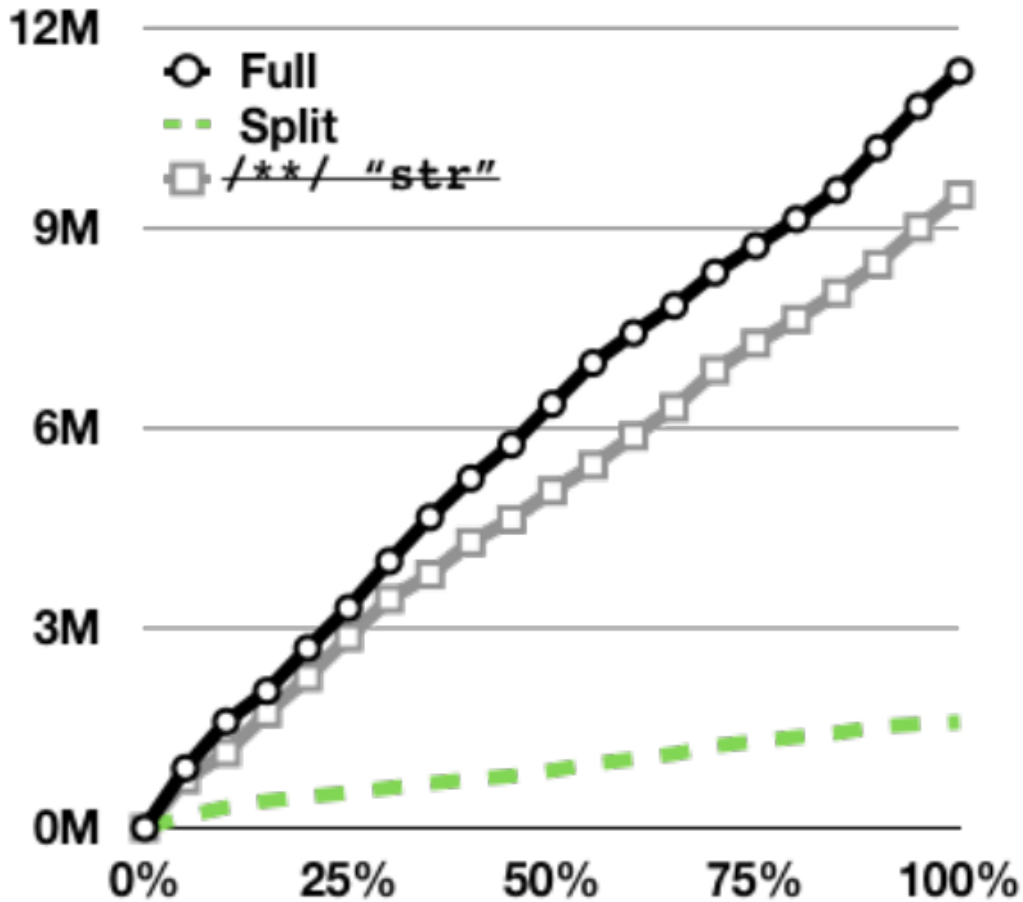
- Fixed by programming language
  - Operators, parentheses, keywords, etc.
- Chosen by developers
  - Identifiers, literals

Vocabulary Problem

- **Large code corpus:**
  Huge number of tokens
- **Difficult to represent and reason about**
- **Relevant for**
  - Models that take code as an input
  - Models that produce code as an output

Vocabulary Problem (2)

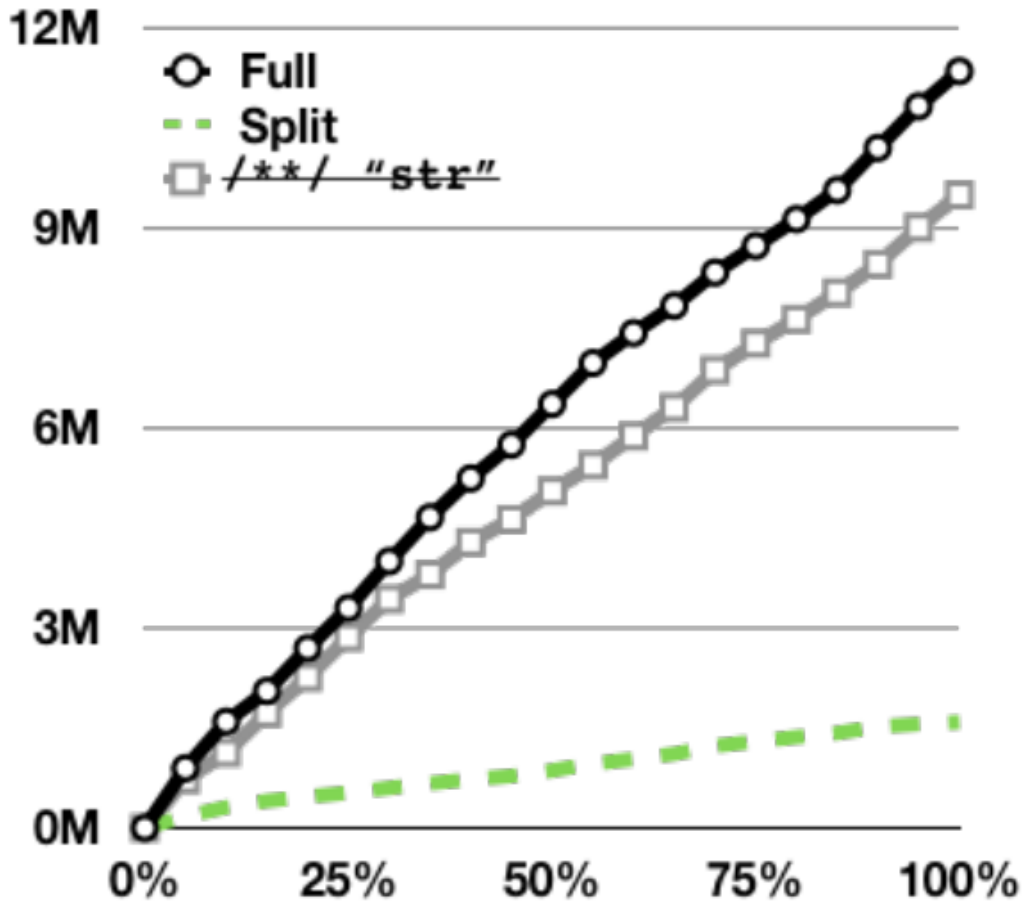
Size of vocabulary for 14k projects



”Modeling Vocabulary for Big Code Machine Learning” (Babii et al., 2019)

Vocabulary Problem (2)

Size of vocabulary for 14k projects



Almost 12 million tokens!

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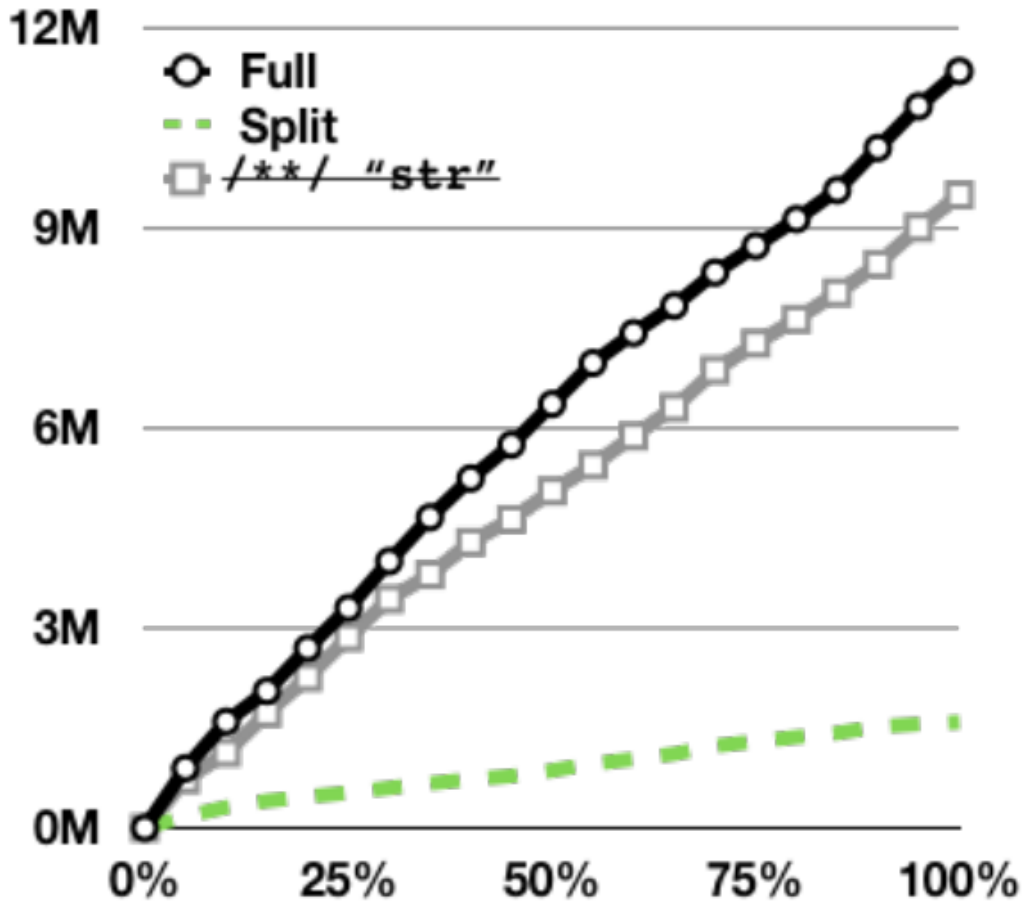
Vocabulary Problem (2)

Size of vocabulary for 14k projects



Replacing comments and strings with placeholders

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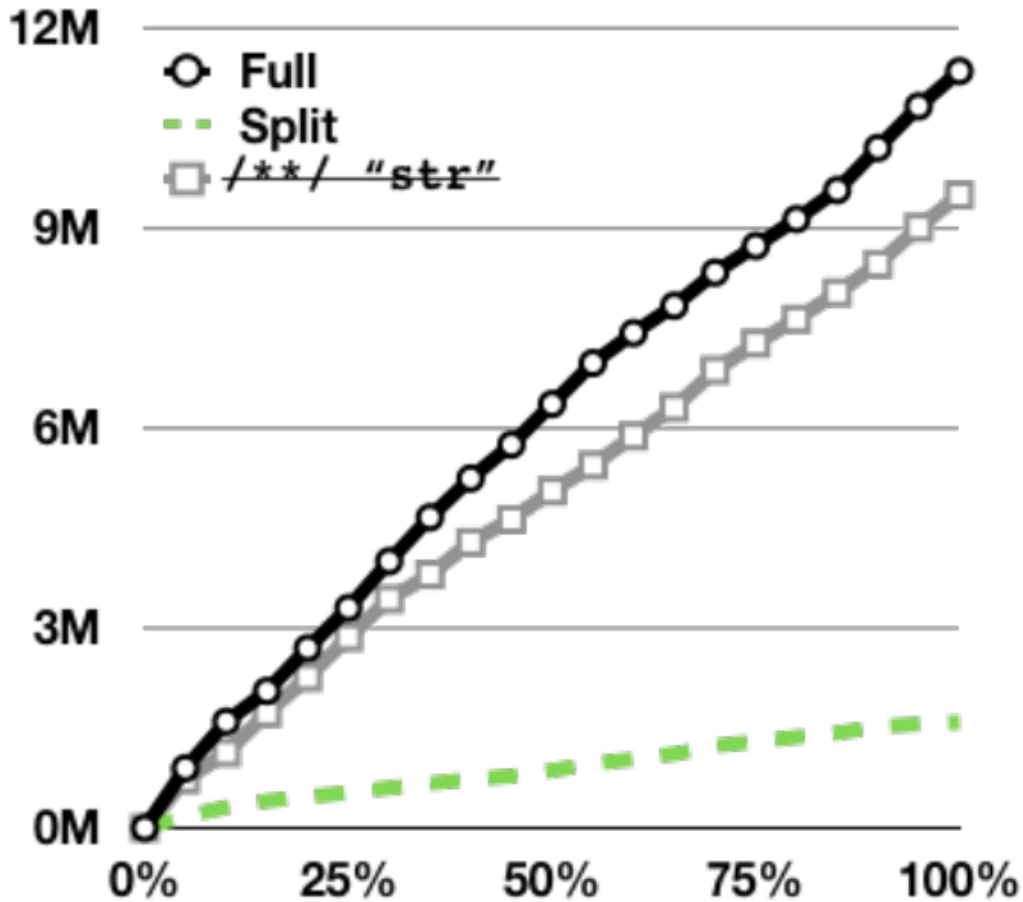
Vocabulary Problem (2)

Size of vocabulary for 14k projects



Split identifiers based on camelCase and snake_case

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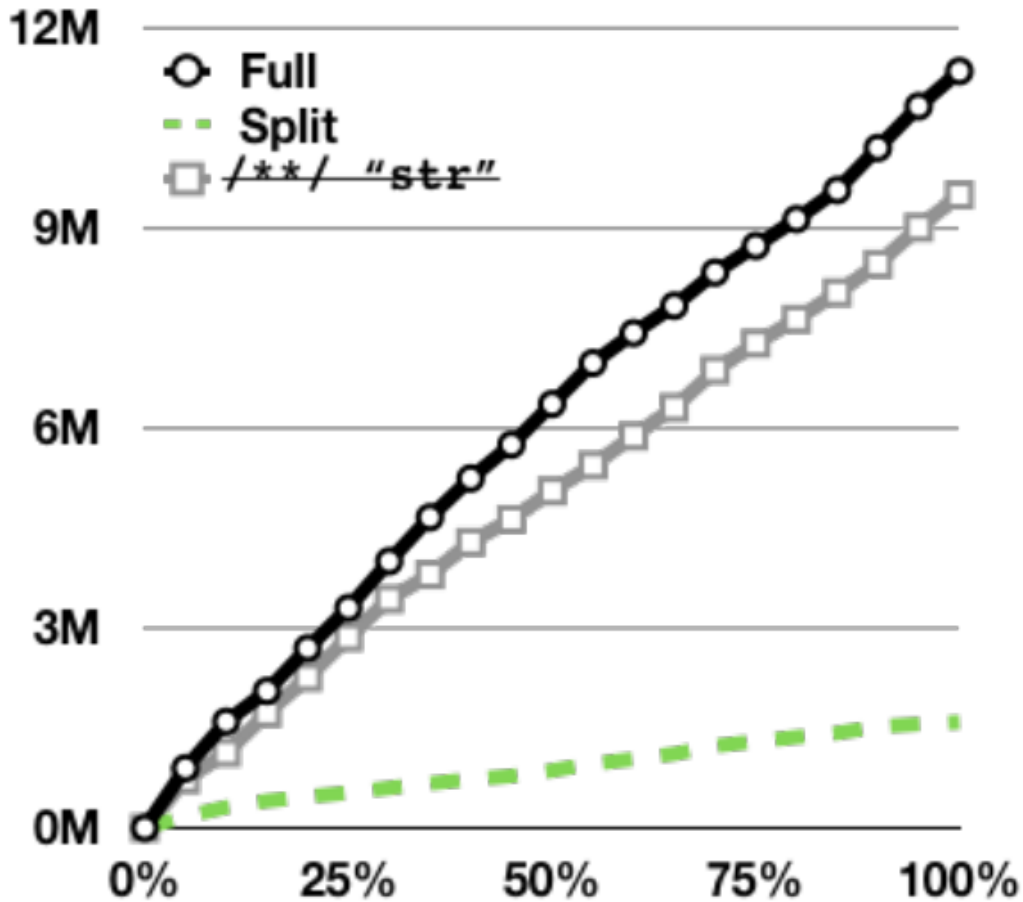
Vocabulary Problem (2)

Size of vocabulary for 14k projects



For all ways of modeling the vocabulary: Linear growth when new projects are added

"Modeling Vocabulary for Big Code Machine Learning" (Babii et al., 2019)

Handling the Vocabulary Problem

Abstract tokens

- Much smaller vocabulary
- Looses valuable informa-tion

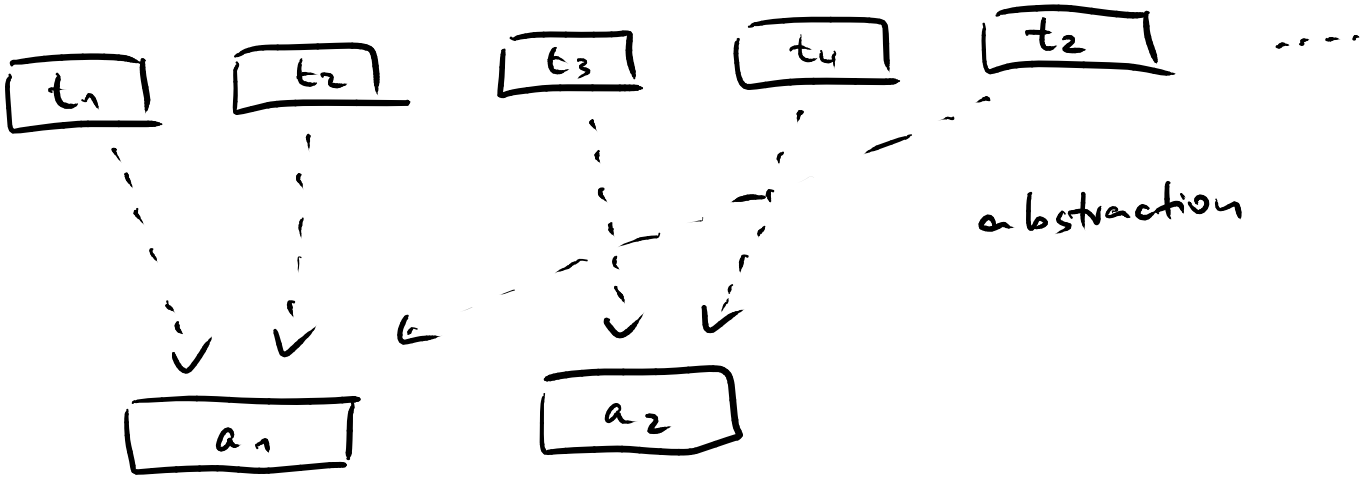
Consider N most frequent tokens only

- Covers large fraction of all tokens
- Out-of-vocabulary problem

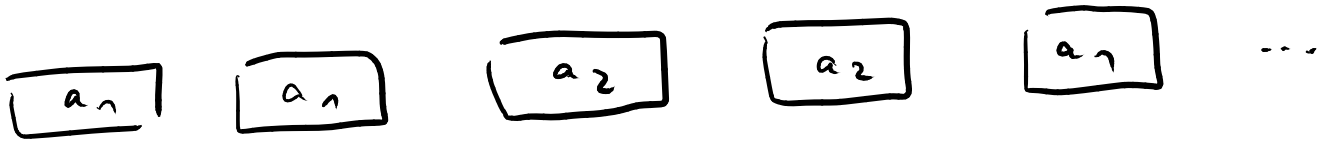
Embed tokens into a vector space

- Constant vector size when code corpus grows
- Non-trivial to obtain an effective embedding

Abstracting Token



Result:



Abstraction based on kind of token

keyword identifier literal

```
if ( file != null ) {
    line = file.read()
}
```

operator op.

keyword operator identifier operator literal ...

OR

```
if ( identifier != null ) {
    identifier = identifier.identifier()
}
```

Consistent Renaming

```
if (file != null) {
    line = file.read()
}
```

↓

```
if ( id1 != null ) {
    id2 = id1. id3()
}
```

Keeping Top-N Tokens

- **Observation: Vocabulary has a "long-tail" distribution**
  - Few tokens occur frequently
  - Many other tokens occur infrequently
- **Keep only N most frequent tokens**
- **Represent others as special "unknown" token**

Keeping Top-N Tokens (2)

Top-N approach on $\approx$ 100k JavaScript files

$\lvert\mathcal{V}_{out}\rvert$	Percentage of unique names covered	Percentage of names covered
1,000	0.40	63.19
5,000	1.99	75.07
10,000	3.97	79.48
20,000	7.95	83.82
30,000	11.92	86.38
40,000	15.89	88.16
50,000	19.87	89.56
60,000	**23.84**	**90.74**
70,000	27.81	91.62
80,000	31.79	92.41
90,000	35.76	93.19
100,000	39.74	93.98

”Context2Name: A Deep Learning-Based Approach to Infer Natural Variable Names from Usage Contexts” (Bavishi et al., 2018)