Function completion in the time of massive data: A code embedding perspective

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ABSTRACT

Code completion is an important feature of integrated development environments (IDEs). It allows developers to produce code faster, especially novice ones who are not fully familiar with APIs and others’ code. Previous works on code completion have mainly exploited static type systems of programming languages or code history of the project under development or of other projects using common APIs. In this work, we present a novel approach for improving current function-calls completion tools by learning from independent code repositories, using well-known natural language processing models that can learn vector representation of source code (code embeddings). Our models are not trained on historical data of specific projects. Instead, our approach allows to learn high-level concepts and their relationships present among thousands of projects. As a consequence, the resulting system is able to provide general suggestions that are not specific to particular projects or APIs. Additionally, by taking into account the context of the call to complete, our approach suggests function calls relevant to that context. We evaluated our approach on a set of open-source projects unseen during the training. The results show that the use of the trained model along with a code suggestion plug-in based on static type analysis improves significantly the correctness of the completion suggestions.

CCS CONCEPTS

- Software and its engineering → Software maintenance tools;

KEYWORDS

software engineering, code completion, language modeling, recommender systems, doc2vec

1 INTRODUCTION

Nowadays, developers rely on features provided by modern Integrated Development Environments (IDEs) to ease their cognitive load and increase their productivity. One purpose of these features is to avoid asking developers to provide information that can be inferred from the available data sources and the current development context [27]. Among these features, code completion is one of the most widely used by, among others, Java developers in Eclipse [28].
suggestion list proposed by a given typing-based code completion system.

To evaluate the proposed approach, we used a corpus of more than 14,000 Java projects from which we extracted more than 10 million function sequences to train our models. To test our completion strategies, we selected 10 projects, not considered for the training, and having more than 160,000 call sites to complete. The results of our evaluation show, on the one hand, that the from-scratch strategy has completion results close to those of Eclipse’s content assist, and that the precision increases with the size of the context, i.e., the number of calls previously performed before the call site. However, these results are insufficient considering the effort made to train the models. On the other hand, the reordering strategy improved the completion precision of Eclipse, for 9 of the 10 projects, by up to 135% reaching 85% of Precision@10. Only the smallest project had lower scores because of the specific vocabulary not seen in the models. To cope with this situation, we explored, with a relative success, the use of subtokens rather than full-function names. Finally, we found that it takes between 700 ms and 800 ms, on average, to produce completion suggestions for a call site. This makes our approach usable in a real programming setting.

The rest of the paper is structured as follows. In Section 2, we introduce the natural language models that we use in this work. Section 3 presents the general approach for building a code completion system based on embedding models and explains its usage for direct completion or integration within an existing typing-based tool. We present the evaluation setup in Section 4 and report on the results in Section 5. Later, we discuss the related work in Section 6. Finally, we draw conclusion and list future work directions in Section 7.

2 BACKGROUND

This section aims to give some intuition about the models that we use in our approach and experiments. We review n-grams language models that allow us to estimate the predictability of our source code dataset. Then, we explain word embedding models to learn vector representations of variable-length texts. In Sections 3 and 3.1, we explain how such model can be used to learn vector representations of source code. We use these representations of code as leverage for the code completion task as described in Section 4.

2.1 n-gram Language Models

Language models (LMs) assign probabilities to sequences of words. A training phase is performed using a set of documents generally written in the same language. The regularities captured by a LM in a training corpus can be used as leverage for performing extrinsic tasks (e.g., speech recognition, spelling correction, text generation...).

Considering a word sequence \( w_1, w_2, \ldots, w_n \), a LM assigns a probability \( P(w_1, w_2, \ldots, w_n) \) to the sequence. We can estimate the probability of the whole sequence using the chain rule of probability:

\[
P(w_1, w_2, \ldots, w_n) = P(w_1)P(w_2|w_1) \cdots P(w_n|w_{n-1}, \ldots, w_2, w_1).
\]

Such a probability is hard to compute because usually long sequences of words are not observed in a training corpus. Therefore, we use n-gram language models to approximate \( P(w_1, w_2, \ldots, w_n) \).

n-gram language models assign a probability to a word \( w \) given an history of size \( n-1 \). n-gram LMs assume that the occurrence of a word depends only on the previous words. In other words, a n-gram model is a Markovian approximation of order \( n-1 \)

\[
P(w_n | w_1, w_2, \ldots, w_{n-1}) \approx \prod_{k=1}^{n} P(w_k | w_{k-n+1}).
\]

For instance, given a bigram model, the probability of a word \( p(w_k | w_{k-1}) \) depends only on the previous word \( w_{k-1} \).

The simplest approach to estimate these word probabilities is a maximum likelihood estimation (MLE) over the raw counts of words in the corpus. For a bigram model, the probability of a word \( w_n \) is

\[
P(w_n | w_{n-1}) = \frac{|w_{n-1}w_n|}{\sum_w |w_{n-1}w|}.
\]

In practice, we do not directly use MLE to avoid the model to assign zero probability to unseen sequences of words. Instead, smoothing techniques assign part of the total probability mass to unseen n-grams. For the purpose of this work, we use Kneser-Ney smoothing that is considered as one of the best smoothing technique [9, 21].

Language model evaluation:

A good language model will predict with high probability the content of a new test sample (e.g., unseen during the training phase). If we consider an English corpus consisting of text documents, a good model will have a low-level of uncertainty when predicting a word sequence in a previously unseen English document. The level of uncertainty of a language model can be measured by the cross-entropy. Given a n-gram language model \( L \) and a word sequence \( w_1^n = w_1, w_2, \ldots, w_n \), the cross-entropy is computed as

\[
H_L(w_1^n) = -\frac{1}{n} \sum_{i=1}^{n} \log P(w_i | w_{i-n+1}).
\]

For the case of a n-gram model, the cross-entropy is the average number of bits required to predict the \( n^{th} \) word given the \( n-1 \) previous words. Consequently, a model that has low entropy on some text documents has a low-level of uncertainty and predicts with confidence the content of the documents.

2.2 Distributed Representations of Words

Word embedding is commonly used in natural language processing (NLP) to learn a mapping of words into an high-dimensional vector space. The notion of word embedding is highly related to distributional semantics. That is quantifying some semantic similarities between words or concepts that appear frequently in the same context in a large corpus of textual data. Two words that have close vector representation are meant to be semantically similar. For example, it is likely that senate and politic would be close.

One of the most-known framework for learning distributed representation of words is Word2vec [25, 26]. Mikolov et al. proposed two neural network architectures that are able to learn vector representation of words from large corpus containing billions of words. The first architecture is called Continuous Bag-of-Words (CBOW). In this architecture, the model learns word representation that can best predict a center word given the surrounding words. The second architecture is called Skip-Gram (SG). Instead of predicting a center word given the surrounding words, the SG model
aims to best predict the surrounding words given the center word. One of the main advantages of Word2vec is that the model is simple and has a low computational cost compared to traditional neural network language models [5].

A Word2vec model is capable of learning embeddings at the word level. Given a training corpus as input, Word2vec learns word representation for each word in the vocabulary. One of the drawbacks of this model is that there is no inherent scheme to the model to learn embedding of sequence of words. Such an approach would, for example, allow us to compute the similarity between two text documents (e.g., of variable size). It would be possible to determine vector representations of sentences with Word2vec by averaging the word vectors of the sentences, but it has been shown to be not efficient. Paragraph vector models aim to tackle this problematic by learning vector representation of variable-length texts.

### 2.3 Paragraph Vector Embedding Model

The paragraph vector (PV) model (Doc2vec) is an extension of Word2vec by Le and Mikolov [23]. PV models learn vector representations (paragraph vectors) of sequences of textual data of variable size (document, phrases, news article...). In this model, each input sequence has a unique corresponding paragraph vector that is learned along with the word vectors. Paragraph vectors are not just concatenation and average of word vectors contained within the paragraph. Instead, paragraph vectors are asked to contribute to a predictive task as for words in Word2vec. There exist two architectures for the learning process: distributed memory (PV-DM) and distributed bag-of-words (PV-DBOW).

- **In PV-DM**, the model randomly sample contexts within the paragraph. The contexts are determined by a window size. Then, an average or concatenation of the paragraph vector and the word embeddings is used to predict the last word of the sampled context. Figure 1 illustrates this architecture.

![Figure 1: PV-DM. The context is randomly sampled using a window size of 4. Words and paragraph embeddings are averaged or concatenated to predict the target word.](image)

- **In PV-DBOW**, the model sample contexts similarly to PV-DM. However, context words are ignored in the input. The paragraph vector is asked to predict random words from the sampled context. This is illustrated in Figure 2.

![Figure 2: PV-DBOW. The context is ignored in the input. The paragraph vector is used to predict the context words.](image)

The advantage of the PV model over Word2vec is that the model is able to learn representation of variable-length texts. As result of the learning phase, the paragraph vectors can capture semantic properties about a whole sequence of textual data. This model has shown to be useful in topic modeling and several NLP tasks [12, 14, 22].

### 3 OUR APPROACH

To illustrate the rationale behind our approach, let us consider the situation in which, Ulwazi, a Java developer, is writing the method

```java
1/ // ...
2 public long size() throws IOException {
3     if (!file.isFile()) {
4         throw new
5         FileNotFoundException(file.toString());
6     }
7     return file.size() // prediction (ctrl+space)
8 }
```

**Listing 1: Motivating example**

Consider also that Ulwazi is coding in an IDE that incorporates, among other features, a code completion plug-in such as Eclipse content assist¹ that suggests function calls. In line 6, after she types `.size()` the plug-in is invoked, and the latter will provide a suggestion list of possible items including function calls that could follow `.size()`. The plug-in exploits static environment information about the currently opened code artefact (e.g., imports, language typing...). The produced suggestion list is generally exhaustive, often long, and ordered alphabetically. Thus, it is more likely that the correct suggestion will not appear at the top of the list, and developers like Ulwazi will waste a valuable time browsing through the list.

Therefore, our objective is to alleviate the burden of developers by providing completion suggestion lists that are: (1) of limited size, and (2) ordered by pertinence so that the correct suggestion is likely to appear in the top positions.

Our approach is based on the hypothesis that there exist recurring function-call patterns in large corpus of source code. Those patterns embody some semantics about high-level concepts, which may appear in different programs with slight linguistic variations. For instance, coming back to the example of the method `.size()` that computes the size of a file, the first step consists in checking whether the input is a file, by calling, for example, a function `.isFile()`. If it is not, one may want to raise an exception with a representation of the file by calling `.toString()`. The final step is to call a function `.length()` that outputs the size of the file. Our approach makes the

¹https://www.eclipse.org/documentation/
assumption that such sequences of function calls are totally or partially recurrent among a lot of projects and that they capture most of the semantics of some higher-level concepts (in our case, “get the size of a file”). By comparing the previous function call sequence (including the method name) “size, isFile, toString” with function call sequences abstracted by an embedding-based language model, it would be possible to determine that “length” is the most probable function call that comes after “file.”

In this work, we propose an approach to learn those high-level concepts and their relationships by training an embeddings model (e.g., paragraph vector model) on a big corpus of code. Once the model trained, we can take advantage of it for the code completion task in two ways: (1) building a suggestion list from scratch or (2) reordering the suggestions made by Eclipse content assist plug-in. We describe the learning process in Section 3.1 and the code completion in Sections 3.2 and 3.3. Figure 3 illustrates both processes.

3.1 Learning Concepts from Code

Word embedding models were originally designed for natural languages. They take as input a corpus of text and output vector representations of words and/or sequences of words (e.g., with paragraph vectors) as a result of the training process. Therefore, to use that kind of model with a programming language, we need to extract useful textual information from the code.

As discussed in the previous section, sequences of function calls embody a great part of the semantics of code. Therefore, it might be a good way to use these sequences as textual representations of the source code. Conversely, syntactical tokens such as if, else, for or a parenthesis carry less domain-specific information and considering them could lead to introducing a lot of noise in the learning, especially in the context of function call completion. It is also important to define how do we cut the code in order to produce sequences of functions and learn the paragraph vectors. We propose to limit the scope of a sequence to a method declaration and its body as for the size method. A method can be seen as a paragraph that is designed to deal with a particular concern, as we would do in a text. And, it is more likely that functions sequences within a small scope are more recurring than in a broader scope, e.g., a whole class. Furthermore, limiting the sequences to a relatively small scope allows the model to learn specific and precise concepts. Our approach is not limited to one specific programming language, any corpus in any programming language can be used.

Our approach is also not limited to using sequences of functions. One alternative would be to consider subtokens of functions instead of the full functions names. Given a function name, the subtokens are words contained within it. For example, if we have a function that is called “convertDateToString”, we tokenize the camel case and the resulting subtokens are ‘convert, date, to, string’. This approach has been used in Allamanis et al.’s previous works [1, 2]. It has shown to be useful to summarize code snippets and for suggesting out-of-vocabulary method declaration names (names that does not appear during the training phase of a model).

The learning process is described in the upper part of Figure 3. The first step extracts function sequences from a corpus of code. Then, the sequences are used as input of a paragraph vector model (Doc2vec). Finally, the model learns high-dimensional vector representations of the function sequences (paragraph vectors).

3.2 Building Suggestion List

In this section, we explain how we can use the paragraph vector model to build a function call completion system from scratch (lower part of Figure 3). For that, we consider again the scenario of Section 3 in which Ulwazi is implementing a class method. The completion process is designed in four steps:

(1) Extraction of the context. The context is made of the name of the method under development followed by the sequence of calls, in the method body, preceding the call site that triggers the completion.

(2) Inferring a paragraph vector. Using the previously trained model, we infer a vector representation of the context (context embedding).

(3) Retrieving the most similar sequences to the context. We use the embedding of the context to retrieve the closest paragraph vectors in the model. This can be done by finding the paragraph vectors that have the greatest cosine similarity to the context vector. Since paragraph vectors correspond to sequences of functions, this is like retrieving the most similar sequences of functions to the context. In our example, we find that three paragraph vectors are similar to the context vector and we retrieve them according to their closeness with the context vector (ranked by decreasing cosine similarity).

(4) Building the suggestion list. We build a suggestion list, either of a fixed-length or depending on the similarity scores, using the retrieved sequences of functions. We iterate over these sequences in decreasing order of similarity. We add functions of the retrieved sequences to the suggestion list and stop when the list has reached its maximum allowed size or a threshold of the similarity score. This step corresponds to the branch 1 in Figure 3.

3.3 Reordering Eclipse’s Suggestions

Building the suggestion list from scratch does not guarantee that the suggestions are feasible in the current project. Instead of building a list of suggestions from scratch, we can reorder the suggestions made by the Eclipse completion plug-in (branch 2 in Figure 3). The advantage of this approach is that Eclipse’s plug-in provides suggestions depending on the packages/libraries imported in the code file in which the method is implemented. Therefore, the reordered suggestion list will only contain tangible function calls.

The process of producing the suggestion list is the same as above, except for the fourth step. In step four, we iterate over the most similar sequences to the context. For each function in a sequence, if the function appears in Eclipse’s suggestion list then we add it to the final suggestion list. We use the same stopping criteria, i.e., fixed length or threshold score. The reordering of Eclipse’s list allow to suggest only function calls that are most likely to occur after the provided context and are correct w.r.t. typing and imports.

4 EVALUATION SETUP

Previous works have shown that source code is (locally) repetitive and predictable using statistical language models [17, 38]. Recent
works have found that variable and function identifiers are the main responsible for the high-level of entropy of code and that syntax tokens artificially increase the source code predictability [33]. Thus, one of the key challenges of learning high-level concepts from codes using sequences of functions lies in the high-level of unpredictability of those sequences. This leads us to address the following research questions:

- **RQ1 [Replication]: How repetitive and predictable are function sequences in source code?**
  We reproduce previous works on naturalness of software [17, 33]. We check whether our datasets satisfy the naturalness hypothesis introduced by Hindle et al. [17]. Then, we ensure that our datasets have a level of cross-entropy in the same order of magnitude than in Rahman et al.’s experiments [33].

- **RQ2: Are paragraph vector embedding models capable of capturing concepts from the code?**
  We evaluate how well the paragraph vector model captures concepts by performing relatedness tests on some functions in the vocabulary of the trained model. The idea is to check whether close functions in the model have consistent embeddings with respect to the semantics of the functions and their usage in the code.

- **RQ3: Using the paragraph vector model, can we accurately suggest function invocations given a context?**
  We use the approach defined in Section 3.2. We evaluate the effectiveness of paragraph vector models for a function call completion task. We use contexts of variable-length sampled from methods of our test projects to produce suggestion lists. We compute metrics defined in Section 4.3 based on the capacity of the model to build suggestion lists that contain relevant function calls.

- **RQ4: Can we use the paragraph vector model in order to improve the suggestion ranking made by Eclipse’s content assist plug-in?**
  We reorder Eclipse’s suggestions using the process defined in Section 3.3. We conjecture that the results will be better than those of RQ3 since we take advantage of existing suggestion lists of Eclipse’s plug-in. As for RQ3, we evaluate our approach using metrics defined in Section 4.3.

## 4.1 Data Source

We use the GitHub Java Corpus [3] consisting of more than 14,000 open-source java projects collected from Github. The corpus’ statistics are presented in Table 1.
Before forming the training sets, we removed 20 projects from the original corpus to build a test set. We select these projects based on their high popularity in Github and to cover a broad range of application domains. We also considered the diversity in size. Table 2 shows statistics for each test project, i.e., the number of methods declared in each test project, the total number of call sites in these methods, and the percentage of function vocabulary that appear in the training dataset. We use the whole 20 projects to answer RQ1 and limit ourselves to the 10 projects in bold to answer the remaining questions. These 10 projects allow us to test the completion for more than 160,000 call sites.

For the training of the n-gram models and the paragraph vector model, we extract more than 10 millions function sequences from the filtered corpus. In Table 3, we specify the number of tokens and word types with and without a minimum count parameter. This parameter is used with paragraph vector model to ignore functions that occur less than a specified threshold (in the experiments, we keep functions that appear at least 20 times in the corpus). The ignored functions are replaced by a common token "UNK". We can observe that when using this minimum count parameter, the number of types decreases drastically (around 7% of types are kept), but the total number of tokens does not decrease that much. This means that there is a significant amount of types that are not frequent among all projects and considering them in the learning phase could lead to learning a lot of noise.

4.2 Evaluating the Paragraph Vector Model

As discussed in our approach, we consider two ways to evaluate the paragraph vector model on function completion tasks. The former is by building a function call completion system from scratch, and the latter is by reordering Eclipse’s suggestions. Both strategies require different inputs that we describe in the next two subsections.

4.2.1 Function Completion from Scratch. For this experiment, we only evaluate the model with full functions sequences. For the evaluation, we follow Schnabel et al. [35] with an intrinsic evaluation that focuses on the relatedness aspect of the paragraph vectors (RQ2), and an extrinsic evaluation that measures the performance of the paragraph vector model on function completion tasks (RQ3).

In the intrinsic evaluation, we pick randomly several functions from the model vocabulary and compute their most similar functions. Then, we check whether close functions embeddings are consistent. We show relatedness results for common and specific functions. For the extrinsic evaluation, for each method under test, we consider the sequence of calls preceded by the method name \((f_1, f_2, ..., f_c, f_{c+1}, ..., f_n)\). Then, we extract the context that will be used for the completion as defined in Section 3.2, by cutting the sequence at a given call, say \(f_c\). In that case, the context is of length \(c\) and the call site to complete is \(f_{c+1}\). We can sample many contexts by varying the size \(c\), i.e., the number calls before the call site to
complete. For each test project, we iterate over the sequences of functions of its methods and extract contexts with size $c \in [1, 8]$. Then, for each context we infer a paragraph vector and build a suggestion list to predict the $(c + 1)$th function call. For the sake of evaluation, we fixed the maximum size of the suggestion lists to 10.

4.2.2 Reordering Eclipse’s Suggestions. For this experiment, we first retrieve the suggestions of the Eclipse content assist plug-in for each call site of each test project. In Table 2, function calls is the number of call sites per project, and then to the suggestion lists retrieved. To reorder these suggestion lists, we experiment with both full function names or subtokens strategies as explained in Section 3.3. For the evaluation with function name subtokens, instead of using the context as is, we tokenize it before inferring a vector representation. As for previous experiment, the maximum size of suggestion lists is 10 to allow comparison between all approaches.

4.3 Effectiveness Metrics
The evaluation aims to determine whether a paragraph vector model is able to efficiently provide good function call suggestion lists. To evaluate our systems, we consider that a set of suggestions is relevant if it reflects the user’s need. That is, the suggestion list contains the correct function call that follows a given context.

To measure the relevance, we calculate two widely-used metrics, precision at $k$ ($P@k$) and the mean reciprocal rank (MRR). As there is a unique valid suggestion for each call site, $P@k$ for a test project is the number of times the expected function call appears in top-$k$ of suggestion lists divided by the number of tested call sites.

The second metric we report is MRR. The reciprocal rank is given by the inverse of the rank of the first relevant suggestion in the result of a test sample. Mean reciprocal rank for a test set $T$ is

$$MRR = \frac{1}{|T|} \sum_{i=1}^{|T|} \frac{1}{\text{rank}_i}$$

where $\text{rank}_i$ is the rank of the first relevant suggestion in the $i$-th test sample. For example, if on average, the relevant function call appears at rank 2, the MRR is 0.5.

5 EVALUATION RESULTS
In this section, we present the results of our experiments and answer the research questions. For the sake of clarity, we present the global results for questions RQ3 – 4 in Table 6 and illustrate them with 5 representative projects for each question.

5.1 Naturalness of Function Calls (RQ1)
Figure 4 shows the average cross-entropy on the 20 test projects including and excluding out-of-vocabulary (OOV) functions, i.e., function names in the project that do not appear in the training set. The cross-entropy for the full functions is much higher than in Hindle et al.’s work. But it decreased by excluding OOV functions and it gets closer to the cross-entropy they reported on a Java corpus of ten projects. Furthermore, we observe that function names subtokens have a significantly lower cross-entropy and that excluding the OOV has no impact. The no decreasing of the cross-entropy when excluding OOV words means that almost all subtokens in the test projects appear in the training set. This means that sequences of functions subtokens are more predictable than sequences of full functions. We conclude that the naturalness hypothesis is more prevalent using subtokens of functions, but we may loose important information about the sharing of semantics across functions.

In their work, Hindle et al. estimated n-gram models on a Java corpus that includes all tokens present in the code. Rahman et al. addressed the same replication work and conclude that syntax tokens are much more present than identifiers in programming languages and that they make the code artificially predictable. The levels of cross-entropy that we report are closer than those reported in Rahman et al.’s work. That is, including only functions in the training set drastically decreases the predictability of the code.

In Figure 5 we report the cross-entropy on 5 test projects using full functions and subtokens functions. We can observe that some projects such as twitter4j and junit have very low cross-entropy, even when considering full functions. This can be explain by the high vocabulary coverage of these two projects (see Table 2). In addition to that, we observe that the subtokens approach yields to a decreasing of the cross-entropy for all test projects. Therefore, we suspect that the paragraph vector model will perform well
| Function                  | Top-3 Most Similar Functions                                                                 |
|---------------------------|---------------------------------------------------------------------------------------------|
| send                      | receive, getAddress, setReplyTo                                                             |
| exists                    | getAbsolutePath, delete, mkdir                                                              |
| getValue                  | getKey, entrySet, size                                                                     |
| assertNotNull             | assertTrue, assertNull, assertEquals                                                        |
| readUnsignedShort         | readUTF8, readClass, readUnsignedByte                                                       |
| getImage                  | setImage, createImage, getColumnImage                                                      |
| deleteNode                | copyNode, createNewNode, getNodeById                                                       |
| getKeyManagers            | getTrustManagers,getDefaultAlgorithm, createSSLContext                                    |

Table 5: Example of function relatedness captured by the embedding model.

on projects that have a high vocabulary coverage and that the subtokens of functions approach could outperform the full functions approach, especially when the coverage of the tested project is low.

5.2 Relatedness of Function Sequences (RQ2)

To address this research question, we first selected the 1,000 function names that the most frequently appear in the training dataset. Then we inspected a random sample of 100. For each, we looked at the top-3 most similar function names in the learned model to check if these are actually related to the considered function name. Table 5 shows examples of the groups of names that we found. Our random inspection showed that the model captures semantic similarities between functions in a consistent way. That is, given a function, the most similar functions are semantically related, and it is reasonable to think that they appear in similar contexts in the code. This is particularly the case for domain-independent function names like those of the 5 first lines of the table. More interestingly, this observation also holds for domain-specific function names such as ones of the three last lines. For instance, for `getKeyManagers`, the model is able to find similar functions related to the concept of encryption. Considering the large size of the training set, we can conclude that there exist regularities in the concepts of the corpus and that our model is capable of capturing them. Thus, we do believe that paragraph vector embedding models can capture high-level concepts from the code (RQ2).

5.3 Function Completion using Paragraph Vector Model (RQ3)

A quick look to Table 6 shows that the results for Doc2vec column are in general close, but less good, as compared to those of Eclipse completion. Except for twitter4j and, to a lesser extent, android-async-http and junit, the Precision@10 (P@10) is lower. This is understandable as this completion strategy does not take into account the list of functions that can be called in the tested project. These results are still interesting, especially when we consider the size of the context used for the completion. Indeed, in Figure 6, we present the evolution of the Precision@10 according to the size of the contexts sampled for 5 tests projects. The curves show that greater contexts increase drastically the precision for all projects. This is explainable because when we provide a large context, the model is able to find more precise sequences of functions in terms of similarity. Fluctuations for game-of-life can be explained by the small size of the project and the lowest percentage of vocabulary coverage (64%). Furthermore, as we suspected in Section 5.1, projects with the highest vocabulary coverage have the highest P@10. This is especially true for twitter4j with P@10 reaching 0.8 for size of contexts of 6. Figure 7 summarizes the results and includes the mean reciprocal rank (MRR) for the 5 projects. We observe that for most projects the MRR is between 0.1 and 0.22, which means that the relevant suggestion appears, on average, between the fourth and the tenth position in the list.

In conclusion, although the performance of this completion strategy is close to one of Eclipse, and that the precision increases with the size of the context, we cannot state that using a paragraph-vector model for call completion is sufficient without considering the specific situation of the project under development.

5.4 Extending Eclipse’s Content Assist (RQ4)

We compare the reordering performance of both paragraph vector models (i.e., with full function names and subtokens) with Eclipse content assist plug-in. As we can see in Table 6, the strategy with full names outperforms clearly the Eclipse baseline both for the Precision@10 and the MRR. The only exception is game-of-life for which the model with subtokens improved slightly the precision of
We identified some threats to the validity and attempted to address them during the design of our evaluation. The first threat relates to the mono-operation bias as we experimented only with Java projects. We conjecture that our approach can be used for call completion in other languages as we do not rely on Java language constructs, but on identifiers. To prevent the mono-method bias, we evaluated our approach with two metrics commonly used to measure the effectiveness of ranking systems. Another threat concerns the interaction of setting and treatment. Indeed, we reused and compared our results with the completion in Eclipse. It has been shown that Eclipse content assist plug-in is commonly used by Java developers [28], and we do believe that it is representative enough. Another important aspect that we considered is the representativeness of the dataset. We made sure to train our models on a large dataset of open-source projects from different domains of application and of variable sizes. For the evaluation, we choose a variety of test projects as well. Finally, an important threat to the validity of our results arises from the choice of hyper-parameters of the paragraph vector models. To address the issue, we followed guidelines from the literature. We tuned the hyper-parameters that influence the most the quality of embeddings\(^2\) and chose commonly used values for the other hyper-parameters, following Lau and Baldwin’s recommendations [22].

6 RELATED WORK

Neural approaches, n-gram and embedding-based language models have been widely used for automating tasks of the software development lifecycle. However, we focus on code completion by contrasting previous works with our approach. Then, we discuss about source code modeling and the broader usage of embedding-based approaches on source code (see the literature study by Chen and Monperrus [11] for more references on these topics).

Code Completion. Code completion has been an active field of research in software engineering. In the first learning-based approach Bruch et al. [7] use k-nearest-neighbors to find relevant suggestions using features extracted from the call site. Later Proksch et al. [32] improve their work by using Bayesian networks and gathering more context information. The main issue of these techniques is that they require to extract features from the code and are designed for particular APIs. In our embedding-based approach, the model learns representations of the source code and is not limited to APIs completion. With the hypothesis of naturalness of software, Hindle et al. [17] outlined the possibility to use n-gram language models for code completion by predicting call sites given the previous code tokens. Tu et al. [38] use cache n-gram language model for code completion by capturing local patterns in the code. Hellendoorn and Devanbu [16] extend this approach by improving the cache component with information about the scope of the call site. Nguyen et al. [31] propose an extension of code completion with n-gram language models by incorporating semantic information about the completion context. These last few works take advantage of the sequential nature of the code to perform code completion without filtering predictable tokens, such as syntax tokens. It has been shown that these tokens make the code artificially predictable [33]. Therefore, even though these experiments show generally good results, they might be overestimated for realistic scenarios where the syntax tokens can be completed using type-based completion tools. Nguyen et al. [29] use AST-based language model to learn higher-level patterns than n-gram language models to improve API code suggestion. Raychev et al. [34] compare the performance of n-gram and neural language models for Android API code suggestion. In our approach, we consider all possible functions calls (not only API) which makes the scope of our completion system broader.

Recent approaches using deep learning have focused mainly on learning representations of AST with attention-based neural networks. Bhoochand et al. [6] use pointer networks to learn long-range dependencies in Python ASTs for identifiers completion in Python. Li et al. [24] use the same approach with a focus on OOV

\(^2\)https://code.google.com/archive/p/word2vec
identifiers. Karampatsis et al. proposed a LSTM neural networks that is able to suggest out-of-vocabulary identifiers by learning the internal structure of code tokens [19]. These last works focus on identifiers completion which is a different scope from our work. Svyatkovski et al. [37] compare several neural network architectures for method and API recommendations in Python. They learn AST-based representations of code snippets to perform the completion by comparing a call site context with the representations learned by their model. In a subsequent paper, Svyatkovski et al. [36] define a framework using the same approach combined with code completion tools to produce a ranking. Alon et al. proposed an approach where a transformer model learns to predict an AST node given all possible AST paths leading to this node [4]. Kim et al. designed the same kind of approach but compared several ways to feed AST trees into a transformer model [20] and focused on the evaluation of their model for predicting specific types of tokens. These two last works reported lower effectiveness than previous works on APIs and identifiers completion due to their broader application scope and are less related to our approach where we focus on function-call completion.

### Source Code Modeling

Recent works for modeling source code have focused on learning probabilistic models of code. Approaches based on n-gram language models have shown to be useful to find regularities in code [16, 17, 31, 38]. More recent approaches are based on distributed representations of source code [18, 23, 25, 26] that learn semantic relationships between code tokens. Both kinds of approaches can be useful for some downstream tasks. Allamanis et al. [1] use embedding-based language model to predict method names. Nguyen et al. [30] learn embeddings of API elements and try to map them across programming languages. Gu et al. [13] propose an embedding approach to find relevant API sequences given a search query. White et al. [39] and Chen and Monperrus [10] use embeddings to find similarities codes for automatic program repair. BÁijch and Andrzejak [8] learn embedding of ASTs of methods for clone detection. These previous works show a broad range of applications in which our embedding-based approach could be used with small adaptations.

### 7 CONCLUSION

In this paper, we presented an approach for function-call completion that can be used alone or integrated with a code completion tool based on a language typing system. Our approach starts from the assumption that it is possible to abstract application-independent high-level concepts in the form patterns of call sequences contained in code repositories. To this end, we build on document-embedding algorithms to train models that can be exploited for function-call completion. Our experiments highlights promising results for most of the tested projects and indicate that our trained model captures useful high-level concepts that can be used for completion. This shows that our approach can be useful for helping developers writing their software even for new projects and with limited knowledge about the used APIs.

Although the obtained results are satisfactory, there is room for improvement. One of the limitations of our approach is that it has a limited efficiency with projects having very specific function names, not frequent in existing code repositories. We plan to improve the natural-language processing pipeline to cope with this situation. We also plan to explore other embedding-based language models to improve the completion. Finally, instead of capturing high-level concepts inside a method scope, we plan to learn similar concepts in wider scopes and thus learning recurring long-range dependencies that could be useful for program summarizing, for instance.

From another perspective, the fact that our approach does not rely on language constructs, but rather on sequences of identifiers used in method names opens the door for many other possibilities to explore. Indeed, we conjecture that the learned models can be reused cross-programming languages. They can also be used, with some adaptation, to assist developers for other tasks such as program documentation by providing summaries, construct naming for automated generation, clone detection, and code search. Finally, an approach similar to ours can be employed to assist in building design diagrams such as those of UML.

### REFERENCES

[1] Miltiadis Allamanis, Earl T. Barr, Christian Bird, and Charles Sutton. 2015. Suggesting Accurate Method and Class Names. In Proceedings of the 2015 10th Joint Meeting on Foundations of Software Engineering (Bergamo, Italy) (ESEC/FSE 2015). Association for Computing Machinery, New York, NY, USA, 381Â–394. https://doi.org/10.1145/2786895.2786849

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| Project         | Size | Eclipse P@10 | Doc2vec MRR | Eclipse + Doc2vec P@10 | Doc2vec + (subtokens) MRR |
|-----------------|------|--------------|-------------|------------------------|---------------------------|
| game-of-life    | 128  | 0.4766       | 0.1786      | 0.1721                 | 0.0388                    |
| android-async-http | 675  | 0.2966       | 0.1134      | 0.3097                 | 0.1144                    |
| clojure         | 13020| 0.6028       | 0.2391      | 0.4306                 | 0.1775                    |
| twitter4j       | 13365| 0.3996       | 0.1659      | 0.636                  | 0.2138                    |
| facebook-android-sdk | 5689 | 0.4379       | 0.1688      | 0.2198                 | 0.0921                    |
| hystric         | 5790 | 0.2038       | 0.0831      | 0.1846                 | 0.079                     |
| junit           | 814  | 0.4169       | 0.1819      | 0.464                  | 0.1237                    |
| antlr           | 11053| 0.3561       | 0.1411      | 0.2889                 | 0.112                     |
| mongo-java-driver | 35836| 0.3734       | 0.1519      | 0.2387                 | 0.1255                    |
| netty           | 72375| 0.3258       | 0.1326      | 0.2303                 | 0.1041                    |

Table 6: Global results of the experiments (RQ3 and RQ4).
