Abstract
During software maintenance, programmers spend a lot of time on code comprehension. Reading comments is an effective way for programmers to reduce the reading and navigating time when comprehending source code. Therefore, as a critical task in software engineering, code summarization aims to generate brief natural language descriptions for source code. In this paper, we propose a new code summarization model named CodeSum. CodeSum exploits the attention-based sequence-to-sequence (Seq2Seq) neural network with Structure-based Traversal (SBT) of Abstract Syntax Trees (AST). The AST sequences generated by SBT can better present the structure of ASTs and keep unambiguous. We conduct experiments on three large-scale corpora in different program languages, i.e., Java, C#, and SQL, in which Java corpus is our new proposed industry code extracted from Github. Experimental results show that our method CodeSum outperforms the state-of-the-art significantly.

Introduction
Source code summarization is the task of creating readable natural language summaries that describe the functionality of software. It is important in the field of source code comprehension. During the software maintenance, programmers spend a lot of time reading and understanding the source code snippets to comprehend them. Studies of program comprehension indicate that programmers often read a summary which is a comment describing the function of the code (e.g., JavaDoc\textsuperscript{1} descriptions for Java methods) or skim source code (e.g., read important keywords) to save time \cite{Rodeghero2014}. For example, Figure\textsuperscript{1} shows a Java method named toIndexName extracted from Github\textsuperscript{2}. Through the summary and name of the method, developers can easily understand the method aiming to “convert the index of an attacker into a readable name in a battle”. However, these summaries are sometimes missing, incomplete or outdated. Therefore, automated source code summarization becomes an emerging technology in software engineering. Predicting these source code summaries can be used in improving code search by natural language queries, code comprehension, and code categorization. At present, a majority of source code summarizations are manual works such as inline comments provided by the programmers or tutorials. However, source code summarization automatically is drastically different from natural language summarization, because unlike natural language, source code is unambiguous and highly structured. Some traditional approaches have tried to give source code summarizations automatically \cite{Haiduc2010, Rodeghero2014, Ying2013}. And some studies applied deep learning models to generate source code summarizations \cite{Iyer2016, Allamanis2016}. The summaries are too short to express the function of given code snippets. The most relative work is \cite{Iyer2016} which proposes an attention-based Recurrent Neural Networks (RNN) model called CODENN. CODENN predicts code comments given source code snippets extracted from StackOverflow\textsuperscript{3}. For translation problem, the performance of RNN is limited. Furthermore, by processing code as plain text, CODENN omits the structural information which is important for program language.

In this paper, we formulate the code summarization task as a translation problem that translates source code to nat-

\textsuperscript{1}http://docs.oracle.com/javase/8/docs/
\textsuperscript{2}https://github.com/
\textsuperscript{3}http://stackoverflow.com/
ural summaries. Our model, CodeSum, shown in Figure 2, adopts an attention-based Seq2Seq model to generate high-level summaries of code snippets. Compare to CODENN, the BLEU score of Seq2Seq model increases to 35.5% (CODENN: 25.3%) on the Java corpus. In order to capture the structural information, AST sequences traversed by SBT are input into CodeSum. By taking the AST sequences as input instead of plain code, the BLEU score of CodeSum increases to 38.17%. We conduct experiments on three largescale corpora in different languages, i.e., Java, C#, and SQL. For source code summarization, we evaluate our model with automatic metrics BLEU-4 (Papineni et al. 2002). The results demonstrate that CodeSum significantly outperforms the state-of-the-art method CODENN (Iyer et al. 2016). The main contributions of this paper are as follows:

- This is the first work using machine translation model to address the task of source code summarization.
- CodeSum adopts AST sequences as input to get structural information. To sequence ASTs, we propose a new approach, SBT, which can express the semantics with structural information and keep unambiguous. In this way, CodeSum can better align source code to the natural language summary, leading to more accurate summary generation.
- Experimental results demonstrate that CodeSum not only significantly outperforms the state-of-the-arts on industry source code but also outperforms on various program languages.

### Related Work

In recent years, some natural language processing (NLP) models have been used in software engineering tasks (eg. code summarization and code completion) because of the naturalness of software (Hindle et al. 2012). (Raychev, Vechev, and Yahav 2014) introduces a statistical language model to synthesize programs with holes using APIs. (Mou et al. 2016) proposes a Tree-Based convolutional Neural Network (TBCNN) based on programs’ AST for programming language processing. (Wang et al. 2016) proposes an approach to leverage n-gram language models to detect bugs. In this work, we explore the application of deep learning techniques to source code summarization.

Some traditional approaches such as topic models and keyword extractor have been used in some studies on generating source code summarization. (McBurney et al. 2014) uses a topic model to select keywords and topics as summaries for source code. (Haiduc et al. 2010) describes one approach based on a Vector Space Model (VSM), in which a summary comprised of the n keywords with the highest term-frequency/inverse-document-frequency scores. (Movshovitz-Attias and Cohen 2013) applies topic models and n-grams to predict class comments. (Ying and Robillard 2013) presents a feasibility study on a supervised machine learning approach that classifies whether a line in a code fragment should be in a summary. (Allamanis et al. 2015) creates a log-bilinear neural network to model code contexts and it suggests method and class names to programmers.

Recently, some studies try giving natural language summaries by deep learning approaches. (Iyer et al. 2016) presents RNN networks with attention to produce summaries that describe C# code snippets and SQL queries. It takes source code as plain text and models the conditional distribution of the summary. The model omits the structural information which is important for code. (Allamanis, Peng, and Sutton 2016) applies a neural convolutional attentional model to the problem that extremely summarizes source code snippets into short, name-like summaries. It aims to generate name-like summaries (average 3 words) which are much shorter than the summaries that CodeSum generates.

In this work, CodeSum uses an attention-based Seq2Seq model with AST sequences to translate source code to natural language. Seq2Seq model is an encoder-decoder model that translates one language to another language. It has achieved remarkable success in various NLP tasks, such as Machine Translation (Cho et al. 2014), Text Summarization (Rush, Chopra, and Weston 2015) and Dialogue System (Vinyals and Le 2015).

### Model

The overall workflow of CodeSum is illustrated in Figure 2. We address the code summarization task to machine translation problem that translates program code to natural language. To get structural information, CodeSum use AST sequences as its input. The AST sequences generated by SBT can not only express the tree structure but also keep no ambiguity. The model mainly contains three components: AST with the SBT traversal, an attention-based Seq2Seq model and a trained model to generate summaries given code snippets. In this section, we mainly introduce the AST with SBT traversal and the Seq2Seq model.

### Abstract Syntax Tree with SBT traversal

CodeSum takes AST sequences as input. To express the structure information and ensure the unambiguous property, we propose a new approach SBT shown in Figure 3 to sequence the ASTs. SBT uses brackets to present a subtree given a node. The procedure of SBT is as follows:

- From the root node, we first use a pair of brackets to represent the tree structure and put the root node itself behind the right bracket, that is (1)1, shown in Figure 3
- Next, traverse the subtrees of the root node and put all root nodes of subtrees into the brackets, i.e., (1(2)2(3)3)1
- Recursively traverse each subtree until all nodes are traversed and get the final sequence (1(2(4)(5)(6)2(3)3)1).

CodeSum processes each AST into a sequence following the steps above. For example, the AST sequence of the following Java method extracted from project Eclipse Che is shown in Figure 4.

```java
/**
 * Extracts request method name bound to request identifier
 */
```
Nodes in boxes denote terminal nodes and the others are non-terminal nodes. Non-terminal nodes specify the structure information of source code. The types of non-terminals may be `ExpressionStatement`, `ReturnTypeStatement`, etc. The leaf nodes correspond to terminal nodes which encode program text. A terminal node not only has a type but also has a value that can be variable names, operators or string, etc. We represent non-terminal and terminal nodes as `T_non` and `T_term.V_term` respectively. `T_non` and `T_term` denote type of non-terminal and terminal nodes respectively. `T_term.V_term` denotes type-value pairs (type-value pair for each each terminal node is connected by `_`) of terminal nodes that occur in high frequency. If `T_term.V_term` is out-of-vocabulary, we use its type `T_term` to represent it. For example, if `SimpleName.extractFor` is out-of-vocabulary, the token will be replaced by `SimpleName`.

```
public String extractFor(Integer id){
    LOG.debug("Extracting method with ID:{}, id);
    return requests.remove(id);
}
```

Seq2Seq

**CodeSum** adopts Seq2Seq translating source code to natural language. The Seq2Seq as shown in Figure 5 consists of a two-layered Long Short-Term Memory (LSTM) to encode AST sequences, and another deep LSTM to decode the target natural language (Sutskever, Vinyals, and Le 2014). Furthermore, we exploit the attention mechanism to learn to align and translate jointly (Bahdanau, Cho, and Bengio 2014).

**Encoder** The encoder is responsible for encoding every AST sequence of Java method into a fixed-size vector. At each time stamp `t`, it reads one token of AST sequence, then updates and records the current hidden state.

\[
h_t = f(h_{t-1}, x_t)
\]

and

\[
c = q(h_1, ..., h_m)
\]

where `h_t` is a hidden state at time stamp `t`, and `c` is a vector generated from the sequence of the hidden states. `f` and `q` are some nonlinear functions where CodeSum use LSTM as `f`. Generally, `q(h_1, ..., h_m) = h_m`, in this paper, CodeSum adopts the attention mechanism which is a recent model that selects the important parts from the input sequence for each target word. Instead of generating target words using the same context vector `c` (`c = q(h_1, ..., h_m) = h_m`), attention mechanism defines individual `c_i` for each target word `y_i` as a weighted sum of all hidden states `h_1, ..., h_m`.

**Decoder** The decoder aims to generate the target sequence `y` by sequentially predicting a word `y_i` conditioned on the context vector `c` and the previous generated words `y_1, ..., y_{i-1}`.

\[
p(y) = \prod_{i=1}^{t} p(y_i | y_1, ..., y_{i-1}, c)
\]

where `y = y_1, ..., y_n` and for each conditional probability is modeled as

\[
p(y_i | y_1, ..., y_{i-1}, x) = g(y_{i-1}, s_i, c_i)
\]
where $g$ is a LSTM that outputs the probability of $y_i$, and $s_i$ is the hidden state of the decoder LSTM for time stamp $i$. The probability is conditioned on a distinct context vector $c_i$ for each target word $y_i$. And $s_i$ is computed by

$$s_i = f(s_{i-1}, y_{i-1}, c_i)$$

The context vector $c_i$ is computed as a weighted sum of hidden state $h_j$ in encoder and computed as:

$$c_i = \sum_{j=1}^{m} \alpha_{ij} h_j$$

The weight $\alpha_{ij}$ of each hidden state $h_j$ is computed as:

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k=1}^{m} \exp(e_{ik})}$$

and

$$e_{ij} = \alpha(s_{i-1}, h_j)$$

is an alignment model which scores how well the inputs around position $j$ and the output at position $i$ match.

**Evaluation**

*CodeSum* is trained on the corpus collected from Github to generate summaries for Java methods and compared with CODENN method introduced in (Iyer et al. 2016).

**Dataset details**

It is important to select high-quality Java projects to extract methods and their JavaDoc descriptions. Therefore, this work selects the projects that have at least 20 stars in 2015 and at least 10 stars in 2016. For each file, we extract Java methods and the first sentence of JavaDoc descriptions. To generate ASTs from the corpus, we use Eclipse’s JDT compiler\(^1\) to parse the Java methods.

However, not every comment is useful, so some heuristic rules are required to filter the data. Non-words or just one-word descriptions are filtered out in this work. And the *setter*, *getter*, *constructor* and *test* methods, which are easy to predict, are also excluded. At last, we get 588,108 pairs and split the dataset into training, valid and testing sets in proportion with 8 : 1 : 1. The average lengths of Java methods and descriptions are 95 and 20 tokens in this corpus.

We add special tokens, *<START>* and *<EOS>* to the training sequences and out-of-vocabulary words in summary sequences are replaced by *<UNK>* token. The vocabulary of AST sequences contains brackets, all types ($T_{non}$ and $T_{term}$) and partial type-value pairs (high-frequency $T_{term}$-$V_{term}$ pairs of terminal nodes). If $T_{term}$-$V_{term}$ is not in the AST dictionary, *CodeSum* uses its type $T_{term}$ instead of $T_{term}$-$V_{term}$ to present the token. Therefore, the *<UNK>* token doesn’t exist in the AST sequences. The AST vocabulary size is 30,000 and natural language vocabulary size is 20,000. We set the maximum length of the AST sequences to 400 tokens, and use special symbol *<PAD>* to pad the shorter sequences. *<START>* token is the first token to generate. According to statistics, the descriptions of more than 85% methods less than 30 tokens, so the maximum summary length in this paper is limited to 30 tokens.

**Training Details**

*CodeSum* is trained on the Tensorflow framework\(^2\) CO-DENN (Iyer et al. 2016) and Seq2Seq models without AST sequences are also trained in this paper. To evaluate the effectiveness of SBT, we exploit two methods to traverse the ASTs, one is traditional traversal method DFS and the other

\(^1\)http://www.eclipse.org/jdt/
\(^2\)https://www.tensorflow.org/
Figure 5: An Illustration of the Seq2Seq Model for code summarization.

Table 1: Evaluation results on Java methods extracted from Github. (CodeSum takes AST sequences as input, and the other models take the plain source code as their input.)

| Models                  | BLEU-4 score(%) |
|-------------------------|-----------------|
| CODENN                  | 25.3            |
| Seq2Seq                 | 34.87           |
| Attention-based Seq2Seq | 35.50           |
| CodeSum (DFS)           | 36.01           |
| CodeSum (SBT)           | 38.17           |

Table 2: Evaluation results on CODENN datasets including C# and SQL programming languages.

| Language | Models     | BLEU-4 score(%) |
|----------|------------|-----------------|
| C#       | CODENN     | 20.4            |
|          | CodeSum    | **30.00**       |
| SQL      | CODENN     | 17.0            |
|          | CodeSum    | **30.94**       |

Accuracy of different models

In this section, we evaluate different models by measuring the BLEU-4 scores on summarizing different programming languages. Specifically, we mainly focus on the following research questions:
- The accuracy of different models for generating summaries given source code.
- The accuracy under different source code lengths or summary lengths.

Results

In this section, we evaluate different models by measuring the BLEU-4 scores on summarizing different programming languages. Specifically, we mainly focus on the following research questions:

- The accuracy of different models for generating summaries given source code.
- The accuracy under different source code lengths or summary lengths.

Accuracy Measure

CodeSum uses BLEU-4 score [Papineni et al. 2002] to measure the accuracy of generated source code summaries. BLEU score is a widely used accuracy measure for machine translation. It computes the n-gram precisions of a candidate sequence to the reference. In this paper, we regard a generated summary sequence as a candidate and a programmer-written summary (extracted from JavaDoc) as a reference.
both methods. For most code lengths, the average BLEU-4 scores of CodeSum improve about 10%. For CodeSum, AST lengths grow rapidly as the source code lengths increase. Therefore, some features will be lost when cutting the long AST sequences into a fixed length sequence.

For different summaries lengths, CodeSum keeps high accuracy along with the increase of summary lengths just as shown in Figure 6(b). However, the accuracy of CODENN decreases sharply while summary lengths growing. When the summary lengths greater than 25 tokens, the accuracy of CODENN decreases to less than 10%. CodeSum still performs better when generates about 25-28 words summarization.

Examples analysis
Table 3 shows some examples of generated summaries given Java methods by CodeSum. Many exactly same summaries are generated by the model no matter the lengths of Java methods (shown in the first two examples). CodeSum performs well when the source code snippets are complex. It learns the structural information such as IfStatement from the AST, and generates accurate descriptions (shown in the examples 2 and 3). It can generate descriptions that contain the information that IfStatement includes. Sometimes there are different descriptions of a source code, and the descriptions may be similar or totally different (shown in the examples 3 and 4). Although the descriptions are different from the targets, they express the methods’ functionality in some degree. Example 3 expresses almost the same meaning as the JavaDoc description. And Example 4 is a shorter summary of this method than the target description. However, the model has limited performances when the descriptions are highly dependent on user identifiers (shown in the last two examples). Each programmer has its own programming style, so the user identifiers are very different even though they express the same meaning. CodeSum can better learn the regular user identifiers when generating summarizations.

Conclusion
This paper formulates code summarization task as machine translation problem which translates program language to natural language. And we propose CodeSum, an attention-based Seq2Seq model, to generate summaries of source code snippets. For capturing the structural information, CodeSum takes the AST sequences as input. Furthermore, we propose a new traversal method SBT to sequence ASTs. SBT can express the semantics of the structural information and keep unambiguous. CodeSum outperforms the state-of-the-art approaches and achieves better results on automatic measure metric named BLEU. And it also achieves satisfactory results not only on industry code (Java methods) but also on some other program languages (i.e., C#, SQL). In future work, we plan to develop better models to deal with user identifiers. And we will explore the other applications of deep learning approaches in software engineering.

References
[Allamanis et al. 2015] Allamanis, M.; Barr, E. T.; Bird, C.; and Sutton, C. 2015. Suggesting accurate method and class names. In Proceedings of the 2015 10th Joint Meeting on Foundations of Software Engineering, 38–49. ACM.
[Allamanis, Peng, and Sutton 2016] Allamanis, M.; Peng, H.; and Sutton, C. 2016. A convolutional attention network for extreme summarization of source code. arXiv preprint arXiv:1602.03001.
[Bahdanau, Cho, and Bengio 2014] Bahdanau, D.; Cho, K.; and Bengio, Y. 2014. Neural machine translation by jointly learning to align and translate. arXiv preprint arXiv:1409.0473.
| Java method                                                                 | Summarization                                                                 | BLEU-4 score(%) |
|----------------------------------------------------------------------------|-------------------------------------------------------------------------------|-----------------|
| public static byte[] bitmapToByte(Bitmap b){                               | Predict: convert Bitmap to byte array                                          | 100             |
|     ByteArrayOutputStream o = new ByteArrayOutputStream();                  | Target: convert Bitmap to byte array                                          |                 |
|     b.compress(Bitmap.CompressFormat.PNG,100,o);                           |                                                                               |                 |
|     return o.toByteArray();                                                |                                                                               |                 |
| private static void addDefaultProfile(SpringApplication app,               | Predict: If no profile has been configured, set by default the "dev" profile. | 100             |
|     SimpleCommandLinePropertySource source){                              | Target: If no profile has been configured, set by default the "dev" profile. |                 |
|     if(!source.containsProperty(                                         |                                                                               |                 |
|         "spring.profiles.active")&&System.getenv().containsKey("SPRING_PROFILES_ACTIVE")|                                                                               |                 |
|         &&app.setAdditionalProfiles(                                      |                                                                               |                 |
|             Constants.SPRING_PROFILE_DEVELOPMENT);                         |                                                                               |                 |
| }                                                                           |                                                                               |                 |
| protected void createItemsLayout(){                                        | Predict: Creates item layouts if any parameters                              | 56.23           |
|     if (mItemsLayout == null){                                             | Target: Creates item layout if necessary                                      |                 |
|         mItemsLayout= new LinearLayout(getContext());                       |                                                                               |                 |
|         mItemsLayout.setOrientation(                                       |                                                                               |                 |
|             LinearLayout.VERTICAL);                                        |                                                                               |                 |
| }                                                                           |                                                                               |                 |
| public void tag(String inputFileName,                                      | Predict: Replaces the message with a given tag                               | 4.56            |
|     String outputFileName,                                                | Target: Tags a text file, each sentence in a line and writes the result to    |                 |
|     OutputFormat outputFormat){                                            |     an output file with a desired output format.                             |                 |
|     List<String> sentences=jsc.textFile(inputFileName).collect();         |                                                                               |                 |
|     tag(sentences,outputFileName,outputFormat);                           |                                                                               |                 |
| }                                                                           |                                                                               |                 |
| public void unlisten(String pattern){                                      | Predict: It can be called when the product only or refresh has ended.        | 0               |
|     UtilListener listener=listeners.get(pattern);                         | Target: Removes a listener that was previously registered with listenForSubscriptions |               |
|     if(listener!=null){                                                   |                                                                               |                 |
|         listener.destroy();                                                |                                                                               |                 |
|         listeners.remove(pattern);                                         |                                                                               |                 |
|     }                                                                    |                                                                               |                 |
| }                                                                           |                                                                               |                 |
| public FactoryConfigurationError(Exception e){                             | Predict: Create a new UNK with a given Exception base cause of the error.    | 90.25           |
|     super(e.toString());                                                  | Target: Create a new FactoryConfigurationError with a given Exception base    |                 |
|     this.exception=e;                                                     |     cause of the error.                                                      |                 |
| }                                                                           |                                                                               |                 |

Table 3: Examples of generated summaries by CodeSum. These samples are necessarily limited to short methods because of space limitations. And AST structure is not shown in the table, because AST is much longer than source code.
[Cho et al. 2014] Cho, K.; Van Merriënboer, B.; Gulcehre, C.; Bahdanau, D.; Bougares, F.; Schwenk, H.; and Bengio, Y. 2014. Learning phrase representations using rnn encoder-decoder for statistical machine translation. arXiv preprint arXiv:1406.1078.

[Haiduc, Aponte, and Marcus 2010] Haiduc, S.; Aponte, J.; and Marcus, A. 2010. Supporting program comprehension with source code summarization. In Proceedings of the 32nd ACM/IEEE International Conference on Software Engineering—Volume 2, 223–226. ACM.

[Haiduc et al. 2010] Haiduc, S.; Aponte, J.; Moreno, L.; and Marcus, A. 2010. On the use of automated text summarization techniques for summarizing source code. In Proceedings of the 2010 17th Working Conference on Reverse Engineering, WCRE ’10, 35–44. Washington, DC, USA: IEEE Computer Society.

[Hindle et al. 2012] Hindle, A.; Barr, E. T.; Su, Z.; Gabel, M.; and Devanbu, P. 2012. On the naturalness of software. In Software Engineering (ICSE), 2012 34th International Conference on, 837–847. IEEE.

[Iyer et al. 2016] Iyer, S.; Konstas, I.; Cheung, A.; and Zettlemoyer, L. 2016. Summarizing source code using a neural attention model. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics, volume 1, 2073–2083.

[McBurney et al. 2014] McBurney, P. W.; Liu, C.; McMillan, C.; and Weninger, T. 2014. Improving topic model source code summarization. In Proceedings of the 22nd International Conference on Program Comprehension, 291–294. ACM.

[Mou et al. 2016] Mou, L.; Li, G.; Zhang, L.; Wang, T.; and Jin, Z. 2016. Convolutional neural networks over tree structures for programming language processing. In Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence, AAAI’16, 1287–1293. AAAI Press.

[Movshovitz-Attias and Cohen 2013] Movshovitz-Attias, D., and Cohen, W. W. 2013. Natural language models for predicting programming comments.

[Papineni et al. 2002] Papineni, K.; Roukos, S.; Ward, T.; and Zhu, W-J. 2002. Bleu: a method for automatic evaluation of machine translation. In Proceedings of the 40th annual meeting on association for computational linguistics, 311–318. Association for Computational Linguistics.

[Raychev, Vechev, and Yahav 2014] Raychev, V.; Vechev, M.; and Yahav, E. 2014. Code completion with statistical language models. In ACM SIGPLAN Notices, volume 49, 419–428. ACM.

[Rodeghero et al. 2014] Rodeghero, P.; McMillan, C.; McBurney, P. W.; Bosch, N.; and D’Mello, S. 2014. Improving automated source code summarization via an eye-tracking study of programmers. In Proceedings of the 36th International Conference on Software Engineering, 390–401. ACM.

[Rush, Chopra, and Weston 2015] Rush, A. M.; Chopra, S.; and Weston, J. 2015. A neural attention model for abstractive sentence summarization. arXiv preprint arXiv:1509.00685.

[Sim, Clarke, and Holt 1998] Sim, S. E.; Clarke, C. L.; and Holt, R. C. 1998. Archetypal source code searches: A survey of software developers and maintainers. In Program Comprehension, 1998. IWPC ’98. Proceedings., 6th International Workshop on, 180–187. IEEE.

[Sutskever, Vinyals, and Le 2014] Sutskever, I.; Vinyals, O.; and Le, Q. V. 2014. Sequence to sequence learning with neural networks. In Advances in neural information processing systems. 3104–3112.

[Vinyals and Le 2015] Vinyals, O., and Le, Q. 2015. A neural conversational model. arXiv preprint arXiv:1506.05869.

[Wang et al. 2016] Wang, S.; Chollak, D.; Movshovitz-Attias, D.; and Tan, L. 2016. Bugram: Bug detection with n-gram language models. In Proceedings of the 31st IEEE/ACM International Conference on Automated Software Engineering, 708–719. ACM.

[Ying and Robillard 2013] Ying, A. T., and Robillard, M. P. 2013. Code fragment summarization. In Proceedings of the 2013 9th Joint Meeting on Foundations of Software Engineering, 655–658. ACM.