CoCoSUM: Contextual Code Summarization with Multi-Relational Graph Neural Network

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Source code summaries are short natural language descriptions of code snippets that help developers better understand and maintain source code. There has been a surge of work on automatic code summarization to reduce the burden of writing summaries manually. However, most contemporary approaches mainly leverage the information within the boundary of the method being summarized (i.e., local context), and ignore the broader context that could assist with code summarization. This paper explores two global contexts, namely intra-class and inter-class contexts, and proposes the model CoCoSUM: Contextual Code Summarization with Multi-Relational Graph Neural Networks. CoCoSUM first incorporates class names as the intra-class context to generate the class semantic embeddings. Then, relevant Unified Modeling Language (UML) class diagrams are extracted as inter-class context and are encoded into the class relational embeddings using a novel Multi-Relational Graph Neural Network (MRGNN). Class semantic embeddings and class relational embeddings, together with the outputs from code token encoder and AST encoder, are passed to a decoder armed with a two-level attention mechanism to generate high-quality, context-aware code summaries. We conduct extensive experiments to evaluate our approach and compare it with other automatic code summarization models. The experimental results show that CoCoSUM is effective and outperforms state-of-the-art methods.

CCS Concepts: • Software and its engineering → Documentation; Maintaining software.

Additional Key Words and Phrases: source code summarization, unified modeling language, graph neural network, transformer

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1 INTRODUCTION

Code summaries (i.e., source code comments) are short natural language descriptions of source code. As it often takes developers much time to read and understand other people’s code, good code summaries can facilitate program comprehension by helping developers quickly understand what a piece of code does. Therefore, code summaries are important for software development and maintenance. However, many developers are not used to write comments and many comments are mismatched, missing, or outdated. For example, Spinellis [Spinellis 2010] found that, in third-party projects ported to the FreeBSD platform, the number of comments per 100 lines varies substantially and even worse, the code of 307 projects has less than one comment per 100 lines. It is thus desirable that source code can be automatically summarized in natural language.

There is a surge of work on automatic code summarization for better program comprehension [Ahmad et al. 2020; Allamanis et al. 2015a, 2016; Fernandes et al. 2018; Fowkes et al. 2016; Haiduc et al. 2010a; Haije 2016; Haque et al. 2020; Hu et al. 2018a, 2019; Iyer et al. 2016; LeClair et al. 2020, 2019; Movshovitz-Attias and Cohen 2013; Sridhara et al. 2010; Wan et al. 2018; Wei et al. 2019, 2020; Zhang et al. 2020]. Rule-based approaches rely on predefined rules or templates [Sridhara et al. 2010] and are thus limited in the types of summaries that can be generated. Information Retrieval (IR) based approaches use similar code snippets to select or synthesize a comment [Haiduc et al. 2010a], thus lacking the capability of learning semantic meanings from existing code. With the accumulation of publicly available source code, data-driven approaches based on deep learning techniques have largely overtaken traditional methods. Recently, inspired by the success of Neural Machine Translation (NMT) [Cho et al. 2014], some researchers have applied NMT models to the code summarization task [Hu et al. 2019; Iyer et al. 2016; LeClair et al. 2019; Wan et al. 2018].

We have noticed that most previous code summarization techniques [Ahmad et al. 2020; Allamanis et al. 2015a, 2016; Haije 2016; Hu et al. 2018a, 2019; Iyer et al. 2016; LeClair et al. 2019; Movshovitz-Attias and Cohen 2013; Wan et al. 2018; Wei et al. 2020; Zhang et al. 2020] only leverage the information (code sequence, AST, etc) within the boundary of the source code method being summarized, which means that only local context has been used. Global contexts, such as the enclosing class (i.e., the class enclosing the target method) and class dependencies, provide important information that local context cannot cover. However, global contexts have not received much attention in source code summarization. From the perspective of Object-Oriented Programming (OOP), a method typically defines an operation conducted by its enclosing class, applying to the class itself or against other classes. The operation’s initiator/receptor classes (e.g., keywords in class name) and their interactions (e.g., class-class level dependence) may be mentioned in a good summary, which is typically outside of the local context of a method. For example, the word resource in the following method summary comes from its enclosing class name Resource:

```java
class Resource {
  ...
  // check whether a resource is occupied
  boolean isOccupied() { return ownerId >= 0; }
}
```

Taking the following code snippet as another example, the word compiler in the method summary comes from class Compiler which the enclosing class Parser extends:

```java
class Parser extends Compiler {
  ...
  // add source code to the compiler
  void addSource(String className, String sourceCode) {
    sourceCodes.put(className, new SourceCode(className, sourceCode));
  }
}
```
Based on such an insight, we argue that leveraging broader context of a source code method would help better summarize the method.

In this paper, we propose CoCoSUM: Contextual Code SUMmarization with Multi-Relational Graph Neural Networks. It addresses the aforementioned limitations of existing work by exploring two global contexts: intra-class level context and inter-class level context. For the intra-class context, we aim to capture the \langle method, class \rangle relationship by using class name information to enrich the generated code summaries. For the inter-class context, we choose the \langle class, class \rangle relationship as the target, which can be represented as a Unified Modeling Language (UML) class diagram. Nodes in a UML class diagram represent classes/interfaces and edges reflect the class-class relationship such as association, realization, dependency, etc.

In our design of CoCoSUM, in addition to the conventional code token encoder and AST encoder as in other approaches [Hu et al. 2018a, 2019; LeClair et al. 2019; Wan et al. 2018], we incorporate intra-class context by using the class name representation learned from a Transformer-based sentence embedding model [Cer et al. 2018]. This is used as an additional encoder to the prevalent two-encoder architecture (i.e., code token encoder and AST encoder). Moreover, we extend the idea of graph neural network GAT [Velickovic et al. 2018] and design a novel Multi-Relational Graph Neural Network (MRGNN) with attention mechanism to encode the inter-class context represented by a UML class diagram.

We conduct extensive experiments on the public dataset CodeSearchNet [Husain et al. 2019] and our newly collected dataset CoCoNet. The results demonstrate that CoCoSUM outperforms the state-of-the-art work with respect to four widely-used metrics (BLEU, ROUGE-L, METEOR, and CIDER). This is because incorporating intra-class and inter-class contexts and combining them with the attention mechanism improve the quality of the generated code summaries. We also perform an extensive ablation study to verify the usefulness of each major component of CoCoSUM. Furthermore, we apply the global contexts to existing representative models and the improved results of these models confirm the generality of the proposed approach. Finally, we perform a human evaluation and the results further confirm the effectiveness of our approach.

We summarize our main contributions as follows:

- To our best knowledge, we are the first to model the two global contexts in automatic code summarization: class names as intra-class context and relationships among classes as inter-class context.
- We propose the Multi-Relational Graph Neural Network (MRGNN) to model the UML diagrams of source code so that inter-class context can be captured.
- We design a novel end-to-end automatic code summarization framework CoCoSUM, which incorporates two novel components: (1) a Transformer-based sentence embedding model for encoding class names and (2) an MRGNN for modeling UML class diagrams.
- Our extensive experiments demonstrate that CoCoSUM outperforms state-of-the-art code summarization methods. Furthermore, the performance of existing code summarization models is also improved after applying the global contexts adopted in CoCoSUM.

The remainder of this paper is organized as follows: Section 2 presents the background. Section 3 introduces the design of CoCoSUM. We present details about our experiment settings in Section 4. We compare CoCoSUM with state-of-the-art works, conduct ablation study, evaluate the stability and generality of CoCoSUM and conduct the human evaluation in Section 5. We discuss the threats to validity in Section 6. Section 7 describes the related work. Finally, we conclude our work in Section 8.
2 BACKGROUND
In this section, we briefly illustrate some background knowledge.

2.1 UML Class Diagrams
The Unified Modeling Language (UML) [Booch et al. 1999; Rumbaugh et al. 1999] is a widely-used language for specifying, visualizing, and documenting the artifacts of a software-intensive system. UML class diagram is a type of static structure diagram that describes the structure of a system by showing the system’s classes and their attributes, operations (or methods), and relationships. In this paper we extract four most common types of relationships expressed by a UML class diagram: generalization, realization, dependency, and association. These relationships are also supported by commonly-used UML tools such as UMLGraph\(^1\).

Figure 1 shows a basic UML class diagram example. The class Car implements the interface Vehicle. The dashed line with a hollow arrow connecting class Car and interface Vehicle indicates the ‘realization’ relationship. The class BMW inherits from the more general class Car. The ‘generalization’ relationship is represented by a solid line with a hollow arrow. Further, a BMW class is associated with its children classes Tyre, Engine and Body. The ‘association’ relationship is represented by a solid line with a solid arrow. The Person class depends on BMW class for its method trip. The ‘dependency’ relationship is represented by a dashed line with a solid arrow.

2.2 Seq2Seq Models
Seq2Seq [Sutskever et al. 2014] is a family of machine learning models, which aims at transforming a sequence into another sequence. Typical applications are machine translation [Cho et al. 2014], text summarization [Rush et al. 2015], image captioning [Vinyals et al. 2015], etc. Seq2Seq approaches are based on an encoder-decoder architecture, with an encoder mapping a source sequence to a

\(^1\)https://www.spinellis.gr/umlgraph/index.html
latent vector and a decoder translating the latent vector into a target sequence. Recurrent Neural Networks (RNNs) [Rumelhart et al. 1986], Long Short-term Memory Networks (LSTMs) [Hochreiter and Schmidhuber 1997], Gated Recurrent Units (GRUs) [Cho et al. 2014], Transformers [Vaswani et al. 2017] or other deep neural networks [Young et al. 2018], which are capable of modeling sequential data, are widely used by the encoder and the decoder in such a design. Furthermore, there are some techniques that are commonly used in the encoder-decoder architecture, including attention mechanism [Vaswani et al. 2017], teacher forcing [Williams and Zipser 1989], etc. Attention mechanism endows the decoder with the ability to process the input sequence selectively. Teacher forcing uses the ground-truth sequences to guide the generation in the training phase.

### 2.3 Graph Neural Networks

The recent advances of deep learning techniques have facilitated many machine learning tasks like object detection, machine translation, and speech recognition [Wu et al. 2020]. The key to such a technology evolution is deep neural networks such as Convolutional Neural Networks (CNNs) [LeCun et al. 2015], which are able to automatically learn the data features instead of heavily relying on the handcrafted features.

Unlike the data that are originally organized in euclidean space (e.g., images on 2D grid and texts in 1D sequence), where CNNs and RNNs can effectively capture hidden patterns, graph data is irregular and each node may have a different number of neighbors. The irregularity of graph data makes some important operations (e.g., convolution), which are easy to compute in euclidean space, difficult for graph data [Wu et al. 2020]. The attempt to extend deep neural networks to graph data has spawned Graph Neural Networks (GNNs) [Wu et al. 2020; Zhou et al. 2018].

The first motivation of GNNs roots in CNNs, since CNNs have a strong ability to learn local stationary structures via localized convolution filter and compose them to form multi-scale hierarchical patterns. Many efforts have been devoted to defining the convolution operation for graph data. This branch of GNNs is therefore called Graph Convolutional Networks (GCNs) and can be divided into spectral methods (defining convolution in spectral domain) and spatial methods (defining convolution in vertex domain).

The prevalence of graph data in real-world makes GNNs applicable to many learning-based systems. Due to the strong ability to learn from graph data, GNNs have achieved great successes in many tasks such as learning chemistry rule and phenomenon [Hu et al. 2020], recommender systems [Wu et al. 2019], document classification [Kipf and Welling 2017], traffic prediction [Zhang et al. 2018], etc.

### 3 COCOSUM MODEL

In this section, we present our model CoCoSUM. As shown in Figure 2, the architecture follows the Seq2Seq framework and includes two main modules, i.e., the encoder module and the decoder module. The encoder module can be divided into two parts: local (method-level) encoder and global (class-level) encoder. The former is responsible for representing the lexical and syntactic information of each method, and the latter encodes the semantic information of each class and the relationship between classes. The decoder integrates the multi-modality representations from the above encoders through an attention mechanism and generates the final summary.

#### 3.1 Local Context Encoders using GRU

Contemporary code summarization approaches mainly leverage local contexts including code tokens and abstract syntax trees (ASTs) to capture the lexical and syntactic information of a code snippet. For the local context encoders, we follow the Ast-attendgru model [LeClair et al. 2019].
We preprocess the code snippets to ASTs and adopt the structure-based traversal (SBT) format [Hu et al. 2018a] to flatten ASTs into sequences. CoCoSUM feeds the code sequence and SBT sequence into a code encoder and an AST encoder, respectively. Both encoders adopt GRU [Cho et al. 2014], but the parameters are not shared:

\[
\begin{align*}
    r_t &= \sigma(W_r x_t + b_r + W_{hr} h_{t-1} + b_{hr}) \\
    z_t &= \sigma(W_z x_t + b_z + W_{hz} h_{t-1} + b_{hz}) \\
    n_t &= \tanh(W_n x_t + b_n + r_t \circ (W_{hn} h_{t-1} + b_{hn})) \\
    h_t &= (1 - z_t) \circ n_t + z_t \circ h_{t-1}
\end{align*}
\]  

(1)
where \( x_t \) indicates the embedding of the \( t \)-th token in either code token sequence or SBT sequence, \( h_t \) is the hidden state for the \( t \)-th token, and \( r_t, z_t, n_t \) indicate the reset, update and new gates, respectively. \( \sigma \) denotes the sigmoid function and “\( \odot \)” is the Hadamard product. \( W_r, W_{hr}, W_z, W_{hz}, W_n \) and \( W_{hn} \) are learnable weight matrices. \( b_r, b_{hr}, b_z, b_{hz}, b_n \) and \( b_{hn} \) are bias vectors.

It is worth noting that the global context encoder can benefit to other local context encoders in other methods (e.g., [Hu et al. 2018a, 2019; Iyer et al. 2016]), as the local context encoder is orthogonal to the global context encoder (illustrated in Sec. 3.2 and evaluated in Sec. 5.4) in CoCoSUM.

### 3.2 Global Context Encoder based on MRGNN

The global context in CoCoSUM contains the intra-class (i.e., class name) and the inter-class (i.e., relationship between classes) information. For the class-class relationship, we extract the UML class diagram that the target method resides in and retain four common relationships: Realization, Generalization, Dependency, and Association. As illustrated in Figure 3, the global context encoder takes two steps to encode global contexts.

Firstly, a class name is preprocessed to a token sequence by the steps described in Section 4.1. Then CoCoSUM generates class name embeddings using the Transformer-based sentence embedding model [Cer et al. 2018] to obtain the class semantic embedding. The sentence embedding model is trained and optimized for greater-than-word length text, such as sentences or short paragraphs on a variety of NL data sources and tasks, and the output is a 512-dimensional vector. The class semantic embedding is a part of the output of the global context encoder, which will be passed to the subsequent GNN module as initial features of the nodes in the UML class diagram.

Secondly, we extract structural relationships from UML and propose MRGNN to encode inter-class context. Specifically, we treat each class as a node and each relationship between two classes as an edge between corresponding nodes. Since there are four types of class relationships, we get four graphs accordingly with each graph containing one of the four relationships. Each class node \( v_i \) has one general node embedding \( h_i^{(g)} \) and four relation-specific embeddings \( h_i^{(r)} \) with \( r \) being one of the four class-class relations. The class semantic embedding \( h_i^{(l)} \), which is generated by the sentence embedding model for class node \( v_i \), is used as the initial hidden state for \( h_i^{(g)} \). The UML graphs have certain characteristics that are rarely considered in general graphs. On one hand, they have multi-relational edges. On the other hand, the definition of each type is relatively broad, resulting in a huge difference in the semantics of edges with the same relationship. For instance, Association relationship may exist between "<Student, Professor>" and also "<Student, Course>", but their semantics are obviously different. Some classic GNN models such as GCN [Kipf and Welling 2017] cannot handle such scenarios. As a comparison, MRGNN is able to capture different relation semantics in UML graphs via inner-attention and outer-attention. The former is mainly used to distinguish the effect of different neighbors in the same relationship, while the latter reflects the influence of different relationships.

To be specific, similar to Graph Attention Network (GAT) [Velickovic et al. 2018], inner attention defines an attention layer to capture the different importance of each neighbor in the same relation \( r \):

\[
\alpha_{i,j}^{(r)} = \frac{\exp\left(\Gamma^{(r)}(W_a^{(r)}h_i^{(r)} \odot W_a^{(r)}h_j^{(r)})\right)}{\sum_{k \in \mathcal{N}_i^{(r)}} \exp\left(\Gamma^{(r)}(W_a^{(r)}h_i^{(r)} \odot W_a^{(r)}h_k^{(r)})\right)},
\]

(2)

where \( \alpha_{i,j}^{(r)} \) is the inner attention coefficient of node \( v_j \) to node \( v_i \), \( h_i^{(r)} \) is the hidden representation of node \( v_i \) for relation \( r \), \( \mathcal{N}_i^{(r)} \) is the first-order neighbors of node \( v_i \) with the relation \( r \), “\( \odot \)” is the concatenation operation, \( \Gamma^{(r)}(\cdot) \) is a single-layer feedforward neural network with a scalar being
the output, and \( W^{(r)}_d \) is a learnable parameter matrix. Given the inner attention coefficient, the hidden representation of node \( v_i \) with respect to the relation \( r \) is:

\[
h_i^{(r)} = \sigma \left( \sum_{j \in \mathcal{N}_i^{(r)}} \alpha_{i,j}^{(r)} W^{(r)}_h h_j \right),
\]

where \( W^{(r)}_h \) is the learnable weight matrix and \( \sigma(\cdot) \) is LeakyReLU.

Outer attention, defined at the relation level, is to aggregate the hidden representations of different relations for each node. The outer attention coefficient of relation \( r \) to node \( v_i \) is defined as:

\[
\beta_i^{(r)} = \frac{\exp( < W_b h_i^{(g)}, W_c^{(r)} h_i^{(r)}> )}{\sum_{r' \in \mathcal{R}} \exp( < W_b h_i^{(g)}, W_c^{(r')} h_i^{(r')}> )},
\]

where “\(<\cdot, \cdot>\)” indicates inner product, \( W_b \) and \( W_c^{(r)} \) are parameter matrices to ensure space alignment, and \( \mathcal{R} \) is the set of the four relationships in UML graphs. Based on the outer attention coefficient, we calculate the updated general node representation as:

\[
h_i^{(g)} = \sigma \left( \sum_{r' \in \mathcal{R}} \beta_i^{(r')} W_d^{(r')} h_i^{(r')} \right).
\]

where \( h_i^{(g)} \) is the output representation of node \( v_i \) in the current MRGNN layer and also the input of the next MRGNN layer when stacking multiple layers, and \( W_d^{(r)} \) is a learnable parameter matrix. Compared to using concatenation and feedforward network in Equation 2, we simply adopt an inner product in Equation 4 due to the small number of UML relationship types. It will help avoid introducing too many parameters and thus causing over-fitting when calculating the attention coefficient. In practice, we stack two MRGNN layers to obtain the class relational embedding.

### 3.3 Attention-based Decoder

Similar to the code token encoder and AST encoder, we deploy GRU as the backbone of the decoder. Additionally, we use a two-level attention mechanism to endow CoCoSUM with the ability to learn from code token sequence, SBT sequence and UML graph selectively.

Let \( H^{(c)} = [h_1^{(c)}, \cdots, h_{T_c}^{(c)}] \), \( H^{(a)} = [h_1^{(a)}, \cdots, h_{T_a}^{(a)}] \) be the outputs from code token encoder and AST encoder, where \( T_c \) and \( T_a \) are the length of code token sequence and SBT sequence, respectively. Firstly, the hidden state \( h_{t}^{(s)} \) of the \( t \)-th summary token is obtained similar to Equation 1. Then the sequential attention [Luong et al. 2015] is used to incorporate the different coefficients between each token in code token sequence (and SBT sequence) and the \( t \)-th summary token, and generate the code context vector \( s_t^{(c)} \) and SBT context vector \( s_t^{(a)} \) for the \( t \)-th summary token:

\[
s_t^{(c)} = \frac{\sum_{i=1}^{T_c} \gamma_{i,t} \cdot h_i^{(c)}}{\gamma_{i,t} = \frac{\exp( < h_i^{(c)}, h_{t}^{(s)}> )}{\sum_{k=1}^{T_c} \exp( < h_k^{(c)}, h_{t}^{(s)}> )}},
\]

\[
s_t^{(a)} = \frac{\sum_{i=1}^{T_a} \delta_{i,t} \cdot h_i^{(a)}}{\delta_{i,t} = \frac{\exp( < h_i^{(a)}, h_{t}^{(s)}> )}{\sum_{k=1}^{T_a} \exp( < h_k^{(a)}, h_{t}^{(s)}> )}}.
\]

We then perform a multi-modal attention to integrate code context, SBT context, intra-class level context \( h_{t}^{(l)} \) (i.e., class semantic embedding) and inter-class level context \( h_{t}^{(g)} \) (i.e., class relational embedding). The integrated encoding vector \( q_t \) for \( t \)-th summary token can be obtained by the following formula:

\[
q_t = \sigma(\lambda_t^{(c)} V_c s_t^{(c)} + \lambda_t^{(a)} V_a s_t^{(a)} + \lambda_t^{(l)} V_l h_{t}^{(l)} + \lambda_t^{(g)} V_g h_{t}^{(g)}),
\]

where \( \lambda_t^{(c)}, \lambda_t^{(a)}, \lambda_t^{(l)}, \lambda_t^{(g)} \) are the learnable weight matrices.
where $\lambda_t = \frac{1}{Z_t} (\lambda_t^{(c)}, \lambda_t^{(a)}, \lambda_t^{(l)}, \lambda_t^{(g)})^T$ is a normalized attention coefficient vector with $Z_t$ being the normalized factor, and $V$ denotes a learnable parameter matrix. To be specific, each entry of vector $\lambda_t$ is defined as:

$$
\left(
\begin{array}{c}
\lambda_t^{(c)} \\
\lambda_t^{(a)} \\
\lambda_t^{(l)} \\
\lambda_t^{(g)}
\end{array}
\right) = \exp\left(
\begin{array}{c}
< V_c s_t^{(c)}, V_s h_t^{(s)}> \\
< V_a s_t^{(a)}, V_s h_t^{(s)}> \\
< V_l h_t^{(l)}, V_s h_t^{(s)}> \\
< V_g h_t^{(g)}, V_s h_t^{(s)}> \\
\end{array}
\right),
$$

(8)

where $V_c, V_s, V_a, V_g$ and $V_l$ are parameter matrices to ensure space alignment.

Given the $t$-th summary token hidden state $h_t^{(s)}$ and the corresponding integrated encoding vector $q_t$, CoCoSUM predicts the probability distribution of the $t$-th summary token as:

$$
y_t = \text{softmax}(f(h_t^{(s)} \oplus q_t)),
$$

(9)

where "⊕" is the concatenation operation and $f(\cdot)$ is a single-layer feedforward neural network. The cross entropy loss is utilized to evaluate the gap between the prediction and the ground truth, i.e.

$$
l = \frac{1}{T_s} \sum_{t=1}^{T_s} < \tilde{y}_t, \log y_t >,
$$

(10)

where $\tilde{y}_t$ is the $t$-th target token by one hot encoding and $T_s$ is the length of the target summary. Many gradient descent based methods can be used for optimizing CoCoSUM and we adopt the adaptive moment estimation method (i.e., AdamW) [Loshchilov and Hutter 2019].

4 EXPERIMENTAL SETUP

4.1 Datasets and Preprocessing

In our experiment, we use two Java datasets: CodeSearchNet [Husain et al. 2019] and CoCoNet (short for Code Comments dataset crawled from interNet). CodeSearchNet is a public dataset containing 542,991 Java methods across the training, validation and test sets. In order to build the UML class diagrams for the programs, project-level source code is needed. Fortunately, the CodeSearchNet dataset provides the url and repo information for each function. We download all the projects (publicly available open-source non-fork GitHub repositories) according to the URLs provided in the data. Then, we filter the dataset according to a set of rules:

1. Code snippets with missing GitHub repositories are removed.
2. Code snippets that cannot be processed by UMLGraph to build UML class diagrams are removed.
3. Summaries shorter than three words are removed.
4. Non-English summaries are removed.

After the above preprocessing steps, we get 267,047 pairs of source code and summaries. Table 1 shows the statistics of the filtered corpus. Following the original partition given in [Husain et al. 2019], the relative size of train:validation:test is set to be 9:0:4:0.6. We have checked that there is no duplication inside or across the training, validation, and test set.

CoCoNet is a large-scale dataset that we collected from GitHub public repositories. We collect Java repositories created during 2015 to 2020 and get 1.8M raw methods. Following Hu et al. [2018a] and Gu et al. [2016], for each method with a comment, we extract the first sentence in its Javadoc as the comment since it typically describes the functionality of the method according to Javadoc guideline [Oracle 2018]. Following Husain et al. [2019] and Hu et al. [2018a], we filter out methods with name ‘toString’, ‘hashCode’, ‘equals’, ‘finalize’, etc and test methods. We also filter out constructors, generated methods and perform dataset deduplication as in [Husain et al. 2019].
Table 1. Statistics of the CodeSearchNet and CoCoNet dataset

| Dataset      | #Repo | #UML Diagram | #Method |
|--------------|-------|--------------|---------|
| CodeSearchNet| 4,116 | 73,856       | 267,047 |
| CoCoNet      | 56,506| 162,543      | 1,228,631|

Fig. 4. Length distribution of code and summary

After the data filtering steps, 1.2M methods are remained at last. The training/validation/test sets splitting of both datasets are by project so that code from the same repository can only exist in one partition. Table 1 shows the statistics of the filtered corpus of CoCoNet. We have made the dataset public.

We use UMLGraph to extract UML class diagrams for extracting the class-class relationships. Four class-class relationships are extracted: realization, generalization, dependency and association (which are represented by IMPLEMENTS, EXTENDS, DEPEND and ASSOC in UMLGraph, respectively). We also apply the following rules to preprocess code and summaries in the dataset:

1. We split code and summary tokens into subtokens by applying the spiral ronin algorithm to reduce data sparsity and then all the tokens are transformed to lower cases.
2. Punctuations in summaries are removed.
3. Numerals and string literals are replaced with the generic tokens `<NUM>` and `<STRING>`, respectively.
4. We use srcml to parse Java methods into ASTs and then flatten them to SBT sequences as described in [Hu et al. 2018a].

For class names used in global context, we preprocess a class name by: (1) splitting by camel case or underscores; (2) removing the `<T>`-like tokens in template classes; and (3) removing parent class name, e.g. `Parent.Child` will be processed to `Child`.

Figure 4 shows the length distribution of code and summaries of CodeSearchNet. We can observe that the length of most code snippets ranges from around 30 to 150 and the length of most summaries ranges from 5 to 15.

4.2 Experiment Setting

The vocabulary size is 10,000 (most frequent words in the training set) for code, summary, and SBT sequences. For UML diagram, we use a 2-layer MRGNN to encode the class-level information. The class embedding size and hidden dimensions of MRGNN are 512 and 256, respectively. For baseline Ast-attgru [LeClair et al. 2019], the embedding size and hidden dimension of GRU are 128 and 256,
respectively. We set the mini-batch size to 256 and a maximum of 40 epochs for each approach. We use the optimizer AdamW [Loshchilov and Hutter 2019] with the learning rate 0.001 for training. To prevent over-fitting, we use Dropout with drop probability 0.5, and Weight Decay with decay ratio 0.3. The experiments are conducted on a server with 2 NVIDIA Tesla V100 GPUs.

4.3 Evaluation Metrics

Similar to previous work [Iyer et al. 2016; Wan et al. 2018; Zhang et al. 2020], we evaluate the performance of our proposed model based on four widely-used metrics including BLEU [Papineni et al. 2002], METEOR [Banerjee and Lavie 2005], ROUGE-L [Lin 2004] and CIDER [Vedantam et al. 2015]. BLEU, METEOR, ROUGE-L and CIDER are prevalent metrics in machine translation, text summarization and image captioning tasks.

BLEU measures the average n-gram precision between the reference sentences and generated sentences, with brevity penalty for short sentences. The formula to compute BLEU-1/2/3/4 is:

$$\text{BLEU-N} = BP \cdot \exp \left( \sum_{n=1}^{N} \omega_n \log p_n \right),$$

where $p_n$ (n-gram precision) is the fraction of n-grams in the generated sentences which are present in the reference sentences, and $\omega_n$ is the uniform weight $1/N$. Since the generated summary is very short, high-order n-grams may not overlap. We use the +1 smoothing function [Lin and Och 2004].

BP is brevity penalty given as:

$$BP = \begin{cases} 1 & \text{if } c > r \\ e^{(1-r/c)} & \text{if } c \leq r \end{cases}$$

Here, $c$ is the length of the generated summary, and $r$ is the length of the reference sentence.

Based on longest common subsequence (LCS), ROUGE-L is widely used in text summarization. Instead of using only recall, it uses F-score which is the harmonic mean of precision and recall values. Suppose $A$ and $B$ are generated and reference summaries of lengths $c$ and $r$ respectively, we have:

$$\begin{cases} P_{\text{ROUGE-L}} = \frac{\text{LCS}(A,B)}{c} \\ R_{\text{ROUGE-L}} = \frac{\text{LCS}(A,B)}{r} \end{cases}$$

$F_{\text{ROUGE-L}}$, which indicates the value of ROUGE-L, is calculated as the weighted harmonic mean of $P_{\text{ROUGE-L}}$ and $R_{\text{ROUGE-L}}$:

$$F_{\text{ROUGE-L}} = \frac{(1 + \beta^2) P_{\text{ROUGE-L}} \cdot R_{\text{ROUGE-L}}}{R_{\text{ROUGE-L}} + \beta^2 P_{\text{ROUGE-L}}}$$

$\beta$ is set to 1.2 as in [Wan et al. 2018; Zhang et al. 2020].

METEOR is a recall-oriented metric that measures how well the model captures the content from the references in the generated sentences and has a better correlation with human judgment. Suppose $m$ is the number of mapped unigrams between the reference and generated sentence with lengths $c$ and $r$ respectively. Then, precision, recall and F are given as:

$$P = \frac{m}{c}, \quad R = \frac{m}{r}, \quad F = \frac{PR}{\alpha P + (1 - \alpha)R}$$

The sequence of mapping unigrams between the two sentences is divided into the fewest possible number of “chunks”. This way, the matching unigrams in each “chunk” are adjacent (in two sentences) and the word order is the same. The penalty is then computed as:

$$\text{Pen} = \gamma \cdot \text{frag}^\beta$$
where frag is a fragmentation fraction: \( \text{frag} = \frac{ch}{m} \), where \( ch \) is the number of matching chunks and \( m \) is the total number of matches. The default values of \( \alpha, \beta, \gamma \) are 0.9, 3.0 and 0.5 respectively.

CIDER is a consensus-based evaluation metric used in image captioning tasks. The notions of importance and accuracy are inherently captured by computing the TF-IDF weight for each n-gram and using cosine similarity for sentence similarity. To compute CIDER, we first calculate the TF-IDF weighting \( g^n(c_i) \) for each n-gram \( \omega_k \) in reference sentence \( s_i \). Here \( \omega \) is the vocabulary of all n-grams. Then we use the cosine similarity between the generated sentence and the reference sentences to compute CIDER score for n-grams of length \( n \). The formula is given as:

\[
\text{CIDER}_n(c_i, s_i) = \frac{\langle g^n(c_i), g^n(s_i) \rangle}{\|g^n(c_i)\| \|g^n(s_i)\|}
\]

where \( g^n(s_i) \) is a vector formed by \( g_k(s_i) \) corresponding to all the n-grams (n varying from 1 to 4). \( c_i \) is the \( i \)th generated sentence. Finally, the scores of various n-grams can be combined to calculate CIDER as follows:

\[
\text{CIDER}(c_i, s_i) = \sum_{n=1}^{N} w_n \text{CIDER}_n(c_i, s_i)
\]

Note that we usually report the scores of BLEU, METEOR and ROUGE-L in percentages since they are in the range of \([0, 1]\). As CIDER scores range in \([0, 10]\), we display them in real values.

5 EVALUATION

In this section, we evaluate CoCoSUM by answering four research questions in Sec. 5.1 to Sec. 5.4. We also describe a case study in Sec. 5.5 and a human evaluation in Sec. 5.6.

5.1 RQ1: What is the effectiveness of CoCoSUM?

We evaluate the effectiveness of CoCoSUM by comparing it to the recent work on code summarization.

- **Code-NN** [Iyer et al. 2016] is the first neural approach that learns to generate summaries of code snippets. It is a classical encoder-decoder framework in NMT that encodes code to context vector with attention mechanism and then generates summaries in decoder.
- **Hybrid-DRL** [Wan et al. 2018] is an improved approach with hybrid code representations (with ASTs) and deep reinforcement learning. It encodes the sequential and structural content of code by LSTMs and tree-based LSTMs and uses a hybrid attention layer to get an integrated representation.
- **H-Deepcom** [Hu et al. 2019] is the SBT-based model, which is more capable of learning syntactic and structure information of Java methods.
- **Ast-attendgru** and **Attendgru** [LeClair et al. 2019] are encoder-decoder network using GRUs with attention. Ast-attendgru is a multi-encoder neural model that encodes both code and AST.
- **Code2seq** [Alon et al. 2019a] represents a code snippet as a set of paths in AST and uses attention to select the relevant paths while decoding.
- **ASTNN** [Zhang et al. 2019] splits large ASTs into sequences of small statement trees, and encodes the trees to vectors by capturing the lexical and syntactical knowledge of statements. We applied the model to code summarization task (original tasks in ASTNN are source code classification and code clone detection).
- **Rencos** [Zhang et al. 2020] enhances the neural model with the most similar code snippets retrieved from the training set. Therefore, it leverages both neural and retrieval-based techniques.
Fig. 5. Comparison on different code lengths and summary lengths

Table 2. Comparison with baselines on CodeSearchNet. The percentages in parentheses indicate the improvement of CoCoSUM over the best baseline.

| MODEL          | BLEU-4 | METEOR | ROUGE-L | CIDER |
|----------------|--------|--------|---------|-------|
| Code-NN        | 12.97  | 7.76   | 19.54   | 0.42  |
| Hybrid-DRL     | 14.14  | 8.47   | 21.09   | 0.64  |
| H-Deepcom      | 14.48  | 9.20   | 22.95   | 0.51  |
| Attendgru      | 17.05  | 12.18  | 27.20   | 0.85  |
| Ast-attendgru  | 17.19  | 12.43  | 27.52   | 0.90  |
| Code2seq       | 15.02  | 8.98   | 23.38   | 0.61  |
| ASTNN          | 17.62  | 10.72  | 27.76   | 0.70  |
| Rencos         | 15.79  | 12.92  | 23.35   | 0.82  |
| NeuralCodeSum  | 14.54  | 10.41  | 27.97   | 0.82  |
| CoCoSUM        | 19.04  | 14.18  | 30.77   | 1.15  |

CoCoSUM        | (8.06%)| (9.75%)| (10.01%)| (27.78%)|

- NeuralCodeSum [Ahmad et al. 2020] models code with Transformer to capture the long-range dependencies and incorporates the copy mechanism [See et al. 2017] to allow both generating words from vocabulary and copying from the input source code.

For baseline comparisons, we re-implement the models of Code-NN and H-Deepcom according to the corresponding papers and use the publicly released code for Hybrid-DRL, Attendgru, Ast-attendgru, Code2seq, ASTNN, Rencos and NeuralCodeSum.
Table 3. Comparison with baselines on CoCoNet. The percentages in parentheses indicate the improvement of CoCoSUM over the best baseline.

| MODEL        | BLEU-4 | METEOR | ROUGE-L | CIDER  |
|--------------|--------|--------|---------|--------|
| Code-NN      | 13.02  | 8.90   | 20.72   | 0.46   |
| H-Deepcom    | 16.29  | 11.86  | 26.40   | 0.74   |
| Attendgru    | 18.55  | 13.80  | 29.28   | 1.11   |
| Ast-attendgru| 18.91  | 13.88  | 29.48   | 1.14   |
| Code2seq     | 14.46  | 9.31   | 23.15   | 0.64   |
| ASTNN        | 16.79  | 9.42   | 25.43   | 0.52   |
| Rencos       | 19.18  | 14.85  | 27.56   | 1.21   |
| NeuralCodeSum| 16.51  | 8.60   | 28.80   | 1.17   |
| CoCoSUM      | 20.15  | 14.94  | 31.24   | 1.30   |

Table 2 shows the performance of different models on CodeSearchNet dataset in terms of four metrics. We compute BLEU scores in the same way as Code-NN [Iyer et al. 2016] and the METEOR, ROUGE-L, CIDER scores as Hybrid-DRL [Wan et al. 2018]. From the table, we can see that CoCoSUM achieves the best scores as marked in bold and improves the best baseline by 8.06% to 27.78% in four metrics. Among all the models, Code-NN is the weakest because it only uses raw code token sequences and fails to capture the semantic and syntax information. Hybrid-DRL is better than Code-NN because it uses AST information and applies reinforcement learning. However, it uses Tree-based LSTM to model the whole tree, leading to gradient vanishing and slow training. It costs around 20 days to train and evaluate this baseline on CodeSearchNet dataset. Therefore, we will omit the comparison to Hybrid-DRL in other experiments. H-Deepcom applies SBT to capture semantic and structural information but the encoded information cannot be fully utilized in the decoding phase. Ast-attendgru combines several types of information including code and SBT to improve summary generation results. ASTNN uses a novel way to split ASTs to better utilize syntactical information. Therefore, Ast-attendgru and ASTNN perform relatively well among all baselines.

To verify the generality of applying CoCoSUM on other datasets, we perform the experiments on our newly collected dataset CoCoNet. As shown in Table 3, CoCoSUM also consistently outperforms all the baselines. One can observe that the performance of Rencos increases a lot on CoCoNet dataset compared to CodeSearchNet. This is because Rencos is a retrieval-based model, as the dataset size increases, it is more likely to retrieve a similar code snippet from the dataset. This observation inspires us to explore adding retrieval module in CoCoSUM in the future work. In summary, the comparison results show that the proposed model CoCoSUM employing global contexts is effective with respect to the four quantitative metrics.

5.2 RQ2: How much do different components/techniques contribute?

5.2.1 Global context ablation study. We implement global contexts by adding the class name and UML channels on top of Ast-attendgru. We do channel ablation study by comparing CoCoSUM\(_c\) (employing intra-class context, CoCoSUM without UML channel) and CoCoSUM\(_u\) (employing inter-class context, CoCoSUM without class name channel) with CoCoSUM (employing both). Table 4 shows that both class name and UML channels improve over Ast-attendgru. Since the functionality of a method is related to its corresponding class, CoCoSUM\(_c\) uses the information of class names to help generate summaries. CoCoSUM\(_u\) uses the inter-class context information by the UML channel to capture the \(\langle\text{class, class}\rangle\) relationship and generate better summaries of source
code. We first obtain the embedding of each node based on the class information and UML graph structure. Then we encode classes based on MRGNN and eventually get the representation of all nodes via the attention mechanism. CoCoSUM as the combination of all channels, further improves CoCoSUM and CoCoSUM, with the UML channel contributing more to the results.

5.2.2 Multi-relational v.s. Single-relational GNN. We use multi-relational GNN model in CoCoSUM, which treats different edges (class relationships) differently. This is because we assume that in UML class diagrams, different neighbor classes of a target class (i.e., the class enclosing the target method) via different relationships may have different impact on summary generation.

To verify the effectiveness of such design, we conduct an ablation study with a single-relational GNN (CoCoSUM) that has the same architecture as CoCoSUM except for treating different class relationships as the same type.

The results in Table 5 show that multi-relational model outperforms the single-relational one, which confirms our assumption.

5.3 RQ3: What is the stability of CoCoSUM?

We analyze the stability of CoCoSUM on code and comments of different lengths. Figure 4 displays the length distribution of code and summary on testing set. The lengths of most code are less than 150 and the lengths of most summaries are less than 30, so we conduct the experiment to evaluate the performance for code lengths varying from 1 to 150 and summary lengths varying from 1 to 30.

Figure 5 presents the performance of CoCoSUM and other models for code and summaries of different lengths. The first column of Figure 5 displays the results of all models for varying code lengths on the four metrics, and the second column displays the results of all models for varying summary lengths on the four metrics. We have the following observations:

- CoCoSUM performs the best on four metrics with varying code lengths.
- CoCoSUM outperforms others with varying summary lengths.
- The performance of baselines decreases when code length increases, while our model performs more stable on all metrics even for longer code.

We conclude that CoCoSUM achieves the best performance on code and comments of different lengths. The performance of CoCoSUM with different code lengths is relatively stable. The performance of CoCoSUM slightly decreases when summary length is increased.
Table 6. Case studies

| Case 1 | public FieldVisitor visitField(  
|        |   final int access,   
|        |   final String name,  
|        |   final String descriptor,  
|        |   final String signature,  
|        |   final Object value) {  
|        |     if (cv != null) {  
|        |         return cv.visitField(access, name, descriptor, signature, value);  
|        |     }  
|        |     return null;  
|        | }  

Enclosing Class Name: ClassVisitor

| Ground Truth | visits a field of the class  
| CoCoSUM | visit a field in the class  
| CoCoSUM_c | visit a field in the given class  
| Ast-attendgru | this method is called when a constant is a member of  
| Attendgru | this method is called when a constant is a member of  
| H-Deepcom | visit a visitor for a the  
| Hybrid-DRL | adds the visitor to the visitor  
| Code-NN | create the visitor to the the the  
| NeuralCodeSum | visit a field visitor  

| Case 2 | public PropertyStatus getProperty(QualifiedName propertyName) throws DAVException {  
|        |     Collection names = new HashSet();  
|        |     names.add(propertyName);  
|        |     URLTable result = getProperties(names, IContext.DEPTH_ZERO);  
|        |     URL url = null;  
|        |     try {  
|        |         url = new URL(locator.getResourceURL());  
|        |     } catch (MalformedURLException e) {  
|        |         throw new SystemException(e);  
|        |     }  
|        |     Hashtable propTable = (Hashtable) result.get(url);  
|        |     if (propTable == null)  
|        |         throw new DAVException(Policy.bind("exception.lookup", url.toExternalForm()));  
|        |     return (PropertyStatus) propTable.get(propertyName);  
|        | }  

Enclosing Class Name: AbstractResourceHandle

| Ground Truth | return the property status for the property with the given name  
| CoCoSUM | return a property status object for the given property name  
| CoCoSUM_c | get a property from the given property  
| Ast-attendgru | get the property value of the property  
| Attendgru | get the property value of the property  
| H-Deepcom | get the property property of the the the  
| Hybrid-DRL | return the property value  
| Code-NN | get the property of the the the  
| NeuralCodeSum | replies the property status for the given property name  

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5.4 RQ4: What is the generality of CoCoSUM?

We analyze the generality of CoCoSUM by applying global contexts to some representative models for code summarization, namely Code-NN, H-Deepcom, Transformer, and Ast-attendgru. We implement it by adding the class names and UML information to these models just as we did for CoCoSUM. Table 7 shows the results for all models are improved accordingly, by the range of 3.2% to 10.8%. This verifies the generality of global contexts.

Moreover, the increasing ratios are in the same magnitude, meaning that the improvement caused by employing global contexts is relatively stable.

The detailed implementation of each compared model is also available online.

5.5 Case study

To conduct a qualitative analysis of our approach, we compare the generated summaries from different models and present two case studies as shown in Table 6. We have the following observations from the results that demonstrate the superiority of our approach:

- In general, CoCoSUM and CoCoSUMc can generate summaries better than other baselines and the summaries of our models are more similar to the ground truth.
- Compared to the baselines, CoCoSUM and CoCoSUMc can generate summary tokens that accurately describe the purpose of the method but cannot be found within the scope of the method. For example, one important summary token should be generated in case 1 is “class” but it cannot be generated only based on the local context (source code itself). CoCoSUM and CoCoSUMc also consider the global context (e.g. the class name “ClassVisitor”). Therefore, they are able to produce better summarization.
- Case 2 shows that CoCoSUM generates the best summary expressing the full meaning of the ground truth. Specifically, the ground truth summary contains a phrase “property status” that cannot be generated by other models. The reason is that the enclosing class of the target method is AbstractResourceHandle, which has a DEPEND relation with class PropertyStatus. This information is learned by our MRGNN module which analyzes the corresponding UML class diagram. One may notice that although the token ‘PropertyStatus’ also appears in the method local context, it is hard for other models to capture this information without the help of global context. The result emphasizes the importance of class-class relationships.

5.6 Human evaluation

We also conduct a human evaluation to investigate our approach’s effectiveness. We follow the previous work [Hu et al. 2019; Iyer et al. 2016; Liu et al. 2018, 2019; Wei et al. 2020] to design the human evaluation from three aspects: similarity of the generated summary and the ground truth summary, naturalness (grammaticality and fluency of the generated summary), and informativeness (the amount of content carried over from the input code to the generated summary, ignoring

| MODEL       | without global contexts | with global contexts |
|-------------|-------------------------|----------------------|
| Code-NN     | 13.37                   | 14.72 (↑ 10.1%)      |
| H-Deepcom   | 15.16                   | 15.65 (↑ 3.2%)       |
| Transformer | 14.62                   | 15.60 (↑ 6.7%)       |
| Ast-attendgru | 17.19               | 19.04 (↑ 10.8%)      |

Implementation of compared models is included in the model folder in the supplementary materials.
fluency). We invite 8 evaluators to assess the quality of summaries generated by CoCoSUM and three baselines Ast-attendgru, ASTNN, and Rencos. The evaluators are software developers or researchers in Company M with more than 5 years of software development experience and fluent English ability. According to Table 2, the baselines we choose are the top ones among all compared methods (we did not choose Attendgru since it is a weaker version of Ast-attendgru).

We randomly select 50 source code examples and the corresponding generated results of the four models from the test set. As illustrated by Figure 6, for each example, we show evaluators its source code link, the ground truth summary, and the generated summary by one of the four models. The evaluators have no idea about which summary is generated by which model. The evaluators are asked to assign scores from 0 to 4 (the higher the better) to measure the informativeness, naturalness, and similarity of the generated summary. We assign 4 evaluators to each question.

The evaluation results are shown in Table 8. Our approach CoCoSUM outperforms Ast-attendgru, ASTNN and Rencos in all three aspects, with average scores 2.44, 3.28, and 2.16 for informativeness, naturalness, and similarity, respectively. Consistent with Wei et al. [2020]'s finding, we find that the scores of informativeness of all methods are higher than those of similarity, indicating that the generated summaries are more relevant to the input code.

---

6Note that the original ASTNN model is not designed for the code summarization task. Therefore, the low score does not directly translate to inferior model.
We also conduct Wilcoxon signed-rank tests [Wilcoxon et al. 1970] for the human evaluation. The results are shown in Table 9. Comparing CoCoSUM with Ast-attendgru, ASTNN, and Rencos, all p-values of Wilcoxon signed-rank tests at 95% confidence level are smaller than 0.01, which mean that the improvements achieved by our approach are statistically significant. In summary, the results of human evaluation confirm the effectiveness of CoCoSUM.

6 THREATS TO VALIDITY

We have identified four main threats to validity.

- We evaluate and compare our work only on Java datasets. Although in principle, the model is not specifically designed for Java, more evaluations are needed when generalizing our work to other languages.
- In the design of a neural network model, there are many orthogonal aspects such as RNN unit type (some papers use GRU, some use LSTM, etc), different token embedding, teacher forcing, etc. When showing the generality of CoCoSUM, we have done the experiments in a controlled way by only adding/removing global contexts. An important future work is to explore variant designs of CoCoSUM such as different token splitting ways, different RNN choice, etc, which has potential to bring further performance improvement.
- The summaries in CodeSearchNet and CoCoNet datasets are collected by extracting the first sentences of Javadoc. Although this is the common practice to place a method’s summary at the first sentence according to the Javadoc guidance [Gu et al. 2016; Hu et al. 2019], there might still exist some mismatched summaries in the dataset. A higher-quality dataset could be used in the future.
- In human evaluation, interrater reliability could be a threat to validity: bias may exist in the scores assigned to the same sample by different evaluators. To mitigate this threat, we explain the meaning of each score carefully to the evaluators before actual scoring. Each generated summary is evaluated by 4 human evaluators, and we use the average score of the four evaluators as the final score. As shown in Table 8, the standard deviations of all methods are very small (ranging between 1.02 to 1.31), meaning that their scores are concentrated and close to each other.

7 RELATED WORK

7.1 Source code representation

Previous work proposed various representations of source code for follow-up analysis [Allamanis et al. 2015a,b; Dam et al. 2016; Gu et al. 2016; Iyer et al. 2016; Ling et al. 2016; Mou et al. 2016; Parisotto et al. 2016; Piech et al. 2015; Sui et al. 2020; Zhang et al. 2019]. For example, Allamanis et al. [2015a]; Sajnani et al. [2016] and Iyer et al. [2016] considered source code as plain text and use traditional token-based methods to capture lexical information. Gu et al. [2016] used the Seq2Seq model originally introduced for statistical machine translation to learn the intermediate vector representations of queries in natural language and then predict relevant API sequences. Mou et al. [2016] proposed a novel Tree-Based Convolutional Neural Network (TBCNN). In TBCNN, program vector representations are learned by the coding criterion; structural features are detected by the convolutional layer; and TBCNN can handle trees with varying children sizes with the continuous binary tree and dynamic pooling.

Dam et al. [2016] built a language model for modeling software code using LSTMs. Ling et al. [2016] and Allamanis et al. [2015b] combined the code-context representation with representations of other modalities (e.g., natural language) to synthesize code. Allamanis et al. [2016]; Hu et al.

7http://www.oracle.com/technetwork/articles/java/index-137868.html
[2018a] apply neural source code representation based on abstract syntax trees and obtain better performance in some programming tasks such as code summarization.

Alon et al. [2019a,b] represented a code snippet as a set of compositional paths in ASTs. Zhang et al. [2019] proposed an AST-based Neural Network (ASTNN) that splits each large AST into a sequence of small statement trees, and encodes the statement trees to vectors by capturing the lexical and syntactical knowledge of statements and apply the representation to tasks such as source code classification and code clone detection. Li et al. [2019] utilized Program Dependence Graph and Data Flow Graph as global context in code representation for bug detection. CoCoSUM differs from it in the contexts that are being utilized and in the target task. Sui et al. [2020] proposed a code embedding method Flow2Vec that embeds control-flows and data-flows of a program in a low-dimensional vector space. The value-flow embedding is formulated as matrix multiplication to preserve context-sensitive transitivity through CFL reachability by filtering out infeasible value-flow paths. Experimental results show that this code representation can improve the performance in code classification and method name prediction task (which was termed as ‘code summarization task’ in their paper). However, their method requires the input program to be compilable (to LLVM in their experiments) therefore restricts the applicable scenarios, where our method CoCoSUM has no requirement on compilation.

7.2 Source code summarization

Popular source code summarization approaches include rule-based, IR-based, and learning-based approaches.

7.2.1 Rule-based and IR-based approaches. In the early stage of automatic source code summarization, rule-based and IR-based approaches are widely used [Eddy et al. 2013; Haiduc et al. 2010a,b; McBurney and McMillan 2014; Rodeghero et al. 2014; Sridhara et al. 2010]. For example, Sridhara et al. [2010] designed heuristics to choose statements from Java methods and use the Software Word Usage Model (SWUM) to identify keywords from those statements and create summaries through manually-defined templates. The summaries are generated according to the function/variable names via these templates. McBurney and McMillan [2014] considered method-level context by choosing important methods that are invoked by the target method via PageRank, and then used SWUM to exact program keywords from the source code and finally generated summaries with a novel natural language generation system. This work uses method-level context (call graph), while we consider different context (class-class relationship).

The basic ideas of IR approaches are retrieving terms from source code for generating term-based summaries or retrieving similar source code and using its summary as the target summary [Eddy et al. 2013; Haiduc et al. 2010a,b; Rodeghero et al. 2014]. Haiduc et al. [2010a,b] used TF-IDF to rank the terms in a method body based on the importance those terms are to that method. TF-IDF gives higher scores to keywords which are common within a particular method body, but rare throughout the rest of the source code. They treat each function of source code as a document and index on such a corpus by LSI or VSM, then the most similar terms based on cosine distances between documents are selected as the summary. Eddy et al. [2013] used topic modeling to improve the work. Rodeghero et al. [2014] use eye-tracking and modify the weights of VSM for better code summarization. Code clone detection techniques were also used to retrieve similar code snippets from a large corpus and reuse their summaries as the targets [Wong et al. 2015, 2013].

7.2.2 Learning-based approaches. Allamanis et al. [2015a] created the neural logbilinear context model for suggesting method and class names by embedding them in a high dimensional continuous space. Allamanis et al. [2016] also suggested a convolutional model for summary generation, which
uses attention over a sliding window of tokens. They summarized code snippets into extreme, descriptive function names.

The NMT-based models are also widely used for code summarization [Haije 2016; Hu et al. 2018a, 2019, 2018b; Iyer et al. 2016; LeClair et al. 2019; Wan et al. 2018]. Iyer et al. [2016] designed a token-based neural model using LSTMs and attention for translation between source code snippets and natural language descriptions. Haije [2016] modeled the code summarization problem as a machine translation task, and some translation models such as Seq2Seq [Sutskever et al. 2014] and attentional Seq2Seq were employed. Hu et al. [2018a] structurally flattened an AST and then passed it on to a standard Seq2Seq model. Hu et al. [Hu et al. 2018b] leveraged API sequences knowledge to improve summary generation with the learned API sequence knowledge. LeClair et al. [2019] designed a multi-input neural network using GRUs and attention to generate summaries of Java methods, which allows the model to learn code structure independent of the text in code. Wan et al. [2018] encoded the sequential and structure content of code by LSTM and tree-based LSTM and used a hybrid attention layer to obtain an integrated representation. The performance was further improved by deep reinforcement learning [Williams 1992] to solve the exposure bias problem during the decoding phase.

Recent work on hybrid approaches [Wei et al. 2020; Zhang et al. 2020], which combine the NMT-based and IR-based methods, shows promising results. These approaches retrieve the most similar code snippets from the training set, encode the code and the retrieved result as context vectors, and decode them simultaneously. For instance, Rencos [Zhang et al. 2020] obtains two most similar code snippets based on the syntax-level and semantics-level information of source code, and uses them to generate the summary. Re2Com [Wei et al. 2020] retrieves the most similar code snippet and the corresponding summary, and then uses the summary as an exemplar to generate the target summary. Haque et al. [2020] utilized the file context of methods (i.e. other methods in the same file) and used an attention mechanism to find words to use in summaries. However, the file context is simply modeled as token sequences of sibling methods and it lacks the class relationship information which is very important for some method summaries.

Compared with the above work, our approach also adopts the general encoder-decoder architecture but incorporates the global contexts into consideration with the help of GNNs, resulting in better performance on source code summarization.

8 CONCLUSION

In this paper, we propose a new code summarization model CoCoSUM, which leverages two types of global context information, i.e., the enclosing class and class relationships, to assist with code summarization. Contemporary automatic code summarization approaches only consider a given code snippet in the local context, without considering its global context information. We firstly represent intra-class context by using transformer-based representation of the name of the class that a given method belongs to, to obtain the class semantic embeddings.

Then we use MRGNN to learn the rich structural information behind the UML class diagrams to obtain the class relational embeddings.

The two embeddings of class names and UML class diagrams are incorporated into a Seq2Seq model with the help of our two-level attention mechanism to enhance the performance of code summarization.

Experimental results have demonstrated the effectiveness of CoCoSUM and confirmed the usefulness of the two global context information.

We believe our work sheds some light on future research by pointing out that source code context including local and global context can play an important role in code summarization. In the future,
we plan to explore more source code information (e.g., call graphs, data flow graphs) to further improve the quality of the generated code summaries.

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