GENERATING SUMMARIES FOR METHODS OF EVENT-DRIVEN PROGRAMS: AN ANDROID CASE STUDY

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ABSTRACT

Developers often dedicate a great amount of time to program comprehension. Program comprehension reduces the cost and time of software development and increases maintainability of a program. However, the lack of documentation makes this process cumbersome for developers. Source code summarization is one of the existing solutions to help developers understand software programs more easily. Lots of approaches have been proposed to summarize source code in recent years. A prevalent weakness of these solutions is that they do not pay much attention to interactions among elements of a software. As a result, these approaches cannot be applied to event-driven programs, such as Android applications, because they have specific features such as numerous interactions between their elements. To tackle this problem, we propose a novel approach based on deep neural networks and dynamic call graphs to generate summaries for methods of event-driven programs. First, we collect a set of comment/code pairs from Github and train a deep neural network on the set. Afterward, by exploiting a dynamic call graph, the Pagerank algorithm, and the pre-trained deep neural network, we generate summaries. We conducted an empirical evaluation with 14 real-world Android applications and 26 participants to measure the quality of our approach. The experimental results show 32.20% BLEU4 and 16.91% METEOR which are a definite improvement compared to the existing state-of-the-art techniques.

Keywords Program Comprehension · Source Code Summarization · Neural Machine Translation · Event-Driven Programs · Deep Learning

1 Introduction

During software development life cycle, diverse documentation such as requirements specification, architecture documents, design documents, bug reports, and so forth are generated. Nevertheless, lack of adequate, up-to-date and qualified documentation is one of the most critical barriers for program comprehension. Xia et al. [1] attest to this fact by claiming that on average developers spend about 58% of their time to understand a program [1]. Source code summarization is one of the solutions to aid developers in understanding programs. Source code summarization is a technique to describe different parts of a software program, namely methods, classes, or packages that provides insight for developers to comprehend the source code more efficiently in terms of speed and effort [2]. Figure 1 illustrates the concept of source code summarization.
// Creates an intent, adds location data to it
// as an extra, and starts the intent service
// for fetching address.
private void startIntentService () {
    Intent intent = new Intent (this, FetchAddressIntentService.class);
    intent.putExtra (Constants.RECEIVER, mResultReceiver);
    intent.putExtra (Constants.LOCATION_DATA_EXTRA, mLastLocation);
    startService (intent);
}

Figure 1: An example of source code summary [3]

Figure 2: An Android application’s life cycle

Many approaches for source code summarization have been proposed over the course of past years. For instance, exploiting knowledge of the crowd [2,4–7], information retrieval [8–10], machine learning [11–15], neural networks [16–18], or even tracking eye-movements of developers [19] are among the approaches for addressing this issue. The main limitation of these approaches is that they do not pay much attention to interactions among elements of a software. McBurney and McMillan [20] regarded context of a program as a critical factor. They determined meaning of a method by considering its invocations. However, the problem is that it does not consider events at all. As a result, these approaches cannot be applied to event-driven programs because of characteristics of those programs such as numerous interactions between their elements. Event-driven programs contain a cycle which waits for events. When an event triggers, the program runs the event. Therefore, interactions among elements are specified at run-time in these programs. An Android application is an excellent example of event-driven programs. Figure 2 demonstrates the life cycle of Android applications.
public class MainActivity extends AppCompatActivity {
    public static final String EXTRA_MESSAGE = "MESSAGE";
    @Override
    protected void onCreate(Bundle savedInstanceState) {
        super.onCreate(savedInstanceState);
        setContentView(R.layout.activity_main);
    }
    public void sendMessage(View view) {
        Intent intent = new Intent(this, DisplayMessageActivity.class);
        EditText editText = (EditText) findViewById(R.id.editText);
        String message = editText.getText().toString();
        intent.putExtra(EXTRA_MESSAGE, message);
        startActivity(intent);
    }
}

public class DisplayMessageActivity extends Activity {
    @Override
    protected void onCreate(Bundle savedInstanceState) {
        setContentView(R.layout.activity_display_message);
        Intent intent = getIntent();
        String message = intent.getStringExtra(MainActivity.EXTRA_MESSAGE);
        TextView textView = findViewById(R.id.textView);
        textView.setText(message);
    }
}

Figure 3: Source code for the running example [21]: the sendMessage() method is called whenever a user clicks the button.

Consider a program presenting one Button and one TextBox in the main display page. A user types an arbitrary text and pushes the Button which leads to another page. The new page shows the user’s text. Figure 3 is a source code that demonstrates the behavior of this program. When a user pushes the Button, functions sendMessage() from the MainActivity class and onCreate() from the DisplayMessageActivity class are invoked, respectively. Unlike how trivial it may seem, this is not an easy task for a Java code. Indeed, when a user pushes the Button, the Android framework calls the onClick() API related to that Button. In other words, the developer must set the onClick attribute to sendMessage for the Button in res/layout/activity_main.xml. Therefore, finding relations between elements statically is a cumbersome task.

In this paper, we try to solve the problem of generating summaries for methods of event-driven programs by extracting interactions between their elements at run-time. To this end, we used a deep neural network to generate summaries. Additionally, to capture interactions at run-time, we utilized dynamic call graphs.

The main contributions of this work are:

1. We propose an approach to generate summaries for methods of event-driven programs. The proposed approach exploits deep neural networks and dynamic call graphs as the key components of the solution to produce meaningful summaries which not only address the semantics of the source code but also have a well-formed grammar.

2. Unlike existing work, we introduce a novel technique for generating summaries that concentrates on run-time execution.

The rest of the paper is organized as follows. In Section 2, we describe our proposed approach. In Section 3, we evaluate the proposed approach by answering seven research questions. We assess our deep neural network model using BLEU4 and METEOR metrics. Furthermore, we set up a user study to evaluate the generated summaries on real-world
Android applications. Next, Section 4 presents threats to the validity of our results. In Section 5, we review related work. Finally, we conclude this paper and present potential future work in Section 6.

2 Proposed Approach

In this section, we present our approach to generate summaries for methods of event-driven programs. We consider the sendMessage() method described in Section 1 as a running example. The running example is used throughout this paper to show our process of generating summaries.

As shown in Figure 4, our proposed approach consists of five steps. In the first step, we extracted a dataset of comment/code pairs from the Github repository. Github is a developing platform for open source projects. Then, applied a few preprocessing tasks on the data such as deleting blank lines, removing code snippets without summaries, and refining code-words based on the Java naming convention. In the second step, we built a deep neural network for the comment/code pairs. This model was used to generate the final summaries. In the third step, we constructed a dynamic call graph of Android applications which were selected to generate summaries for. In the fourth step, the PageRank algorithm was applied to the graph mentioned above. In the end, using our deep neural network of step two and outputs of the PageRank algorithm, we generated human-readable summaries for the selected methods of applications. In the following, we will elaborate more on the steps of our approach.

![Figure 4: An overview of the proposed approach for Android applications](image)

2.1 Step1: Preprocess Data

In this part, we elucidate the first step of our approach. First, a preprocess will be applied to comment/code pairs extracted from the Github website. Hu et al. [18], extracted more than 500 thousand comment/codes pairs from Github and applied a few heuristic methods to extract 69708 pairs from this data. Although the 500 thousand pairs are available online, the prepossessed data are not accessible. As a result, we explored their raw data as a starting point. These source codes are written in Java, and Java programs follow specific naming conventions. The main preprocess steps used in this study are:

1. First, the blank lines (\n) and tabular characters (\t) were removed and replaced by space character.
2. Afterward, we identified and tokenized words with all capital letters that came before words that had capital first-letters. For instance, The following regular expression does the above task:

```
// SQLDatabase --> SQL Database
// Regular Expression: [A-Z]+(?=[A-Z][a-z])
```

3. Furthermore, words with capital first-letters or all lowercase letters are extracted as well. The corresponding regular expression comes as follows:

```
// Regular Expression: [A-Z]?[a-z]+
```

4. Finally, we extracted words that all their letters were capital. We also kept special tokens in the final preprocessed data.
public void sendMessage(View view) {
    ... 
    startActivity(intent); 
}

(a) Output of the first step on the running example

public void sendMessage(View view) {
    ... 
    startActivity(intent); 
}

(b) Output of the second step on the running example

public void onClick(View view) {
}

(c) Pass the highest node block as an input to the pre-trained model

(d) Generated summaries for the given method

Figure 5: The outputs of applying different steps of the proposed approach on the running example

Figure 5a demonstrates the output of our running example after the first step.

2.2 Step2: Train a Deep Neural Network

Recently, researchers have turned to applying deep learning methods to various fields of software engineering such as commit message generation [22, 23], intention mining [24], and code search [25]. Among these fields, is code summarization via deep learning [18], which has attained promising results so far. In this part, we describe our proposed deep neural network. The deep neural network is used as a pre-built model to generate final summaries. We followed the notation described at the deeplearning.ai video tutorial [26]. The notation of our deep model is as follows:

- $x$: set of source codes written in Java programming languages.
- $x^{(i)}$: $i$th source code in the set of $x$.
- $x^{(i)}_t$: $t$th token in the above sequence.
- $T_s$: $T$ is the length of the sequence $s$.
- $y$: set of comments written in natural language.
- $y^{(i)}$: $i$th comment in the set of $y$.
- $y^{(i)}_t$: $t$th term in the above sequence.

Our deep neural network tries to translate $x^{(i)} = (x^{(i)}_1, x^{(i)}_2, ..., x^{(i)}_{T_s})$ to $y^{(i)} = (y^{(i)}_1, y^{(i)}_2, ..., y^{(i)}_{T_y})$ for every $i$ in a comment/code pair. Figure 6 demonstrates the architecture of our proposed deep neural network. The architecture consists of three components, namely encoder, decoder, and attention mechanism. In the following, we describe each component in detail.
2.2.1 The Encoder

There have been many pieces of research on the semantic representation of terms in a vector format with real numbers, namely Continuous Bag of Words (CBOW) [27], SKIP-GRAM [28–30], and Global Vectors (GLOVE) [31]. The benefit of this approach is that as much as the terms are semantically similar, their vectors are similar as well. Therefore, we used one embedding layer in the encoder and decoder components, for which the weights are tuned during the deep neural network learning phase. However, to reduce the learning time and to obtain more accurate weights, we used the pre-built model introduced in the Glove website [32].

One simple solution to avoid overfitting is to use dropout [33]. Dropout randomly omits neural network units. We used dropout = 0.2 in the neural network layers similar to Luong et al. research [34]. Recurrent Neural Network (RNN) is suitable for sequences of inputs [35]. RNN generates sequence \( y = (y_1, y_2, \ldots, y_T) \) from input sequence \( x = (x_1, x_2, \ldots, x_T) \). During the learning phase, RNN computes the weights using equation (1),

\[
\begin{align*}
    h_t &= \sigma(W_h[h_{t-1}, x_t] + b_h) \\
    y_t &= W_h h_t + b_y \\
    T_x &= T_y
\end{align*}
\]

(Eq. 1)

where function \( \sigma \) is calculated using equation (2):

\[
\sigma(z) = \frac{1}{1+e^{-z}}
\]

(Eq. 2)

Vanishing gradient is a problem in simple RNNs [36]. Vanishing gradient happens when a gradient is very small, and hinders changing values of weights and even can stop the neural network’s training. To solve this issue, various methods such as Gated Recurrent Unit (GRU) [37] and Long Short-Term Memory (LSTM) [38] have been proposed. We applied the latter in this work similar to Luong et al. study [34]. LSTM is calculated using equation (3):

\[
\begin{align*}
    \tilde{c}_t &= \tanh(W_c[h_{t-1}, x_t] + b_c) \\
    \Gamma_u &= \sigma(W_u[h_{t-1}, x_t] + b_u) \\
    \Gamma_f &= \sigma(W_f[h_{t-1}, x_t] + b_f) \\
    \Gamma_o &= \sigma(W_o[h_{t-1}, x_t] + b_o) \\
    c_t &= \Gamma_u \ast \tilde{c}_t + \Gamma_f \ast c_{t-1} \\
    h_t &= \Gamma_o \ast \tanh(c_t)
\end{align*}
\]

(Eq. 3)

Unidirectional RNNs use only past data. However, knowing about the future helps as well. Bidirectional RNNs (BRNN) process sequences on both directions and two different layers [39]. In the learning process, weights are computed using
equation (4):

\[
\hat{h}_t = \sigma \left( W_{\overrightarrow{h}} \left[ \hat{h}_{t-1}, x_t \right] + b_{\overrightarrow{h}} \right) \\
\hat{h}_t = \sigma \left( W_{\overleftarrow{h}} \left[ \hat{h}_{t-1}, x_t \right] + b_{\overleftarrow{h}} \right) \\
y_t = W_y \left[ \hat{h}_t, \hat{h}_t \right] + b_y
\]  
(Eq. 4)

Graves and Schmidhuber [40], combined bidirectional recurrent neural networks with LSTM. Moreover, one can stack layers of neural networks to build a deep network [41]. We have used a stack of BRNNs on top of the embedding layer in the encoder element.

2.2.2 The Decoder

Decoder generates summaries. We aim at finding the sequence \( y = (y_1, y_2, \ldots, y_{T_y}) \) from the sequence \( x = (x_1, x_2, \ldots, x_{T_x}) \), given that it applies in equation (5):

\[
\arg \max_y = \prod_{t=1}^{T_y} P(y_t|x, y_1, y_2, \ldots, y_{t-1}) 
\]  
(Eq. 5)

One approach is to test all possible cases, which is definitely costly, with the computational complexity of \( O(|V|^T_y) \) (\(|V|\) denotes the vocabularies’ set size). Another approach is to use a greedy search algorithm. These algorithms select a term that maximizes the value of \( P(y_t|x, y_1, y_2, \ldots, y_{t-1}) \) in each step. However, if one utilizes a greedy search algorithm, she cannot change the term in the future. Furthermore, greedy search algorithms do not guarantee to produce good results since the co-occurrence probability of some terms is higher than others.

A better solution is to exploit the beam search algorithm [42]. In the beam search algorithm, the \(|B|\) top probabilities, are recorded partially for every step. \(|B|\) denotes as the width of the beam. Suppose \(|B| = 3\) and \(|V| = 100\). At first, one needs to compute \( P(y_1|x) \) for each term, that is 100 probabilities for different values in the dictionary. Then she selects the three highest probabilities. Next, for every three terms, she computes the probability \( P(y_2|x, y_1) \) for all the cases in which \( y_2 \) is equal to one of the vocabularies’ set. It results in \(|B| \times |V| = 3 \times 100 = 300\) number of computed probabilities. She should again select the three highest probabilities among these 300 values. Next, for each of these three phrases, she computes the probability \( P(y_3|x, y_1, y_2) \) for all the cases in which \( y_3 \) is equal to one of the vocabularies’ set. The same as above, she will have another 300 probabilities. In the next steps, the algorithm is applied similarly as before until the final step, in which a summary with the highest probable value is selected as the output summary.

This heuristic algorithm does not necessarily optimize results; however, its computational complexity equals to \( O(|B| \times |V|) \) which is immensely faster than computing all cases. It is worth mentioning that if \(|B| = 1\), this heuristic algorithm acts like a greedy one. As \(|B|\) increases, the quality of generated summaries improves, however, the learning time rises as well.

2.2.3 The Attention Mechanism

Recently, the sequence-to-sequence model has yielded valuable results in the neural machine translation [43]. In the traditional sequence-to-sequence model [44], the decoder uses the last hidden state of the encoder as an input for generating the output sequence (Figure 7). In other words, all the information about encoder is stored in \( h_{T_x}\).
Information integration in $h_{T_x}$ causes some problems. For example, to produce the output, it needs to remember the whole input. $y_t$ focuses on all the input terms, however, it is better to pay more attention (give more weights) to some parts of the input. To mitigate this problem, the attention mechanism was introduced. The attention mechanism was first used by Graves in his work [45]. Afterward, other researchers proposed different variations of this mechanism in their studies [46,47]. In this work, a modified version of the attention mechanism introduced by Bahdanau et al. [46], was applied.

In the encoder element, we used a stack of BRNNs. Suppose there are $l$ layers, and $\overrightarrow{h_j^{[l]}}$ and $\overleftarrow{h_j^{[l]}}$ are the forward and backward states of the RNN for the term $t$. Therefore, $h_j^{[l]}$ is computed as $h_j^{[l]} = [\overrightarrow{h_j^{[l]}}, \overleftarrow{h_j^{[l]}}]$. We defined a context matrix denoted as $C$. $C_i$ is the $i$th column of the context matrix and is called a context vector. $C_i$ indicates how much attention the output term $y$ pays to the terms of input sequence $x = (x_1, x_2, \ldots, x_{T_x})$. In other words, each of the members of $x = (x_1, x_2, \ldots, x_{T_x})$ to what extent attributes to generating the output $y_i$. States of the RNN of the decoder element are denoted as $S_i$. $\alpha_{ij}$ represents how much should $y_i$ of the decoder element (the $i$th term of the summary) pay attention to $h_j^{[l]}$ of the decoder element (the $j$th term of the code). Figure 8 depicts the relationship between the attention mechanism and the decoder element in the RNN state.

Figure 8: The relationship between the attention mechanism and the decoder element

Figure 9 describes the structure of attention unit. According to Figure 9, the context vector $C_i$ is calculated based on equation (6). Equation (7) computes the attention weights.

$$C_i = \sum_{j=1}^{T_x} \alpha_{ij} h_j^{[l]}$$  \hspace{1cm} (Eq. 6)

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k=1}^{T_x} \exp(e_{ik})}$$  \hspace{1cm} (Eq. 7)

The next step is to train a model on the preprocessed data, which will be used to generate summaries in the final step.

**Implementation details** for the deep neural network are discussed in this part. The operational environment for the deep neural network was the Ubuntu16.04. Our hardware included 40 processing cores and 64GB RAM. We used Tensorflow library to build the neural network model [48] and Pandas library to preprocess the data [49]. Embedding

\footnote{The idea of this figure is adapted from a video created by Halthor. The video is available online at https://youtu.be/W2rWtgXJBZU.}
layers included vectors with dimensions of 300. If the input word already exists in the pre-built model, its weights from the model are used. Otherwise, the corresponding vector to the input word is initialized with uniformly distributed real numbers between -1 and 1. The pre-built model contains about 2.2 million words.

The maximum length of summaries and codes are set to 35 and 100 tokens, respectively. In cases where the length of the input code is less than 100, remaining elements of the vector are replaced with zeros. Moreover, four words are pre-allocated namely (PADDING, 0), (UNK, 1), (SOS, 2), and (EOS, 3). UNK refers to an unknown word, which means the word does not exist in the deep neural network dictionary. Furthermore, SOS and EOS represent the start and end of each sentence, respectively.

In the learning process of deep neural networks, the goal is to minimize the loss function. We have used cross-entropy loss function in this study. The set of generated summaries is represented by \((y^{(1)}, y^{(2)}, \ldots, y^{(N)})\), in which \(N\) is the number of generated summary and \(y^{(i)}\) denotes as the \(i\)th generated summary. Therefore, the cross-entropy loss function can be calculated using equation (8):

\[
\mathcal{L} = \sum^{N}_{i=1} \sum^{T_{y^{(i)}}}_{t=1} - \log P\left(y^{(i)}_{t} | y^{(i)}_{1}, y^{(i)}_{2}, \ldots, y^{(i)}_{t-1}\right)
\]

\[\text{(Eq. 8)}\]

Exploding gradient is one of the problems with long sequences. To prevent this, given that the gradient’s size is more than a specific threshold such as \(\tau = 5\), one should decrease its value using the approach introduced by Pascanu et al. \[50\]. In other words, its value should be updated using equation (9):

\[
\hat{g} \leftarrow \frac{\tau}{||g||} \hat{g}
\]

\[\text{(Eq. 9)}\]

Adam is used for parameters’ optimization \[51\]. As suggested Kingma and Ba study \[51\], we used \(\beta_1 = 0.9\), \(\beta_2 = 0.999\), and \(\epsilon = 10^{-8}\) as default input values for Adam algorithm.

Overfitting is another problem that may occur while applying machine learning techniques. It happens when a technique matches too closely with a specific set of data. Therefore, rendering the aforesaid technique unfit for predicting other data sets reliably. To avoid overfitting, we randomly split the deep model’s inputs into three categories, namely train (80%), valid (10%), and test (10%) set.

We generated checkpoints for every epochs during the training phase. Then, the best model for validation set was selected (in terms of BLEU score) to evaluate on the final test set.
2.3 Step 3: Create a Dynamic Call Graph

Event-Driven programs depend on the occurrence of events at run-time. Consider the running example illustrated in Section 1. The method `sendMessage()` is invoked every time a user clicks the `Button`. However, it is not a trivial task to find out why pushing the button is followed by running the `sendMessage()` method. In this step, we tackle this problem by leveraging the power of dynamic call graphs. Yuan et al. [52], proposed an approach to generate a dynamic call graph for Android applications. Authors created a tool named Rundroid to create these graphs. This tool not only considers invocations between methods in static time but also recognizes messages transferred between an application and the Android framework at run-time. However, the Rundroid lacks automation, and users have to manually run and test programs to generate call graphs. Therefore, to automatize this task through generating random test with desired time intervals, we used a tool developed by Google, known as Monkey [53]. Figure 10 depicts a part of dynamic call graph generated for the running example.

![Call Graph of the Running Example](image)

Figure 10: Call graph of the running example

2.4 Step 4: Apply PageRank

The PageRank algorithm was developed by Page and Brin [54] to sort webpages based on their popularity in Google’s search engine. McBurney et al. [20] used the same concept for measuring the importance of different methods. Similarly, we applied the PageRank algorithm to the dynamic call graph generated in the previous step. The PageRank algorithm plays a crucial role in the proposed approach. Therefore, we dedicate the following part to discussing this algorithm.

Consider the dynamic call graph of Figure 10. This graph consists of 13 nodes denoted as \( V = \{n_1, n_2, n_3, \ldots, n_{13}\} \) and 12 edges. Damping factor, denoted as \( d \), indicates how likely is it for a specific node to be visited through time. It is
conventional to set $d = 0.85$ [55]. The PageRank algorithm assigns a rank to each node. These ranks determine the importance of nodes in the corresponding graph. Ranks are calculated using equation (10) [54] which $r_i$ shows the rank of $n_i$:

$$r_i = (1 - d) + d \times \sum_{n_j \in B_i} \frac{r_j}{l_j} \quad \text{(Eq. 10)}$$

In equation (10), $l_i$ is the number of outgoing edges from $n_i$ and $B_i$ is the set of nodes which have outgoing edges to $n_i$. For instance, Table 1 shows results of the PageRank algorithm applied to the running example.

| $l_i$ | $B_i$ | $r_i$ |
|------|------|------|
| 1    | {}   | 0.0545 |
| 4    | {1}  | 0.1009 |
| 1    | {2}  | 0.0717 |
| 5    | {3}  | 0.1155 |
| 0    | {2}  | 0.0717 |
| 0    | {2}  | 0.0717 |
| 0    | {4}  | 0.0792 |
| 0    | {4}  | 0.0792 |
| 0    | {4}  | 0.0792 |
| 0    | {4}  | 0.0792 |

2.5 Step5: Generate Summaries

In this step, final summaries are generated from the pre-trained model and ranks of nodes in the dynamic call graph produced in the second and fourth steps, respectively. To this end, methods of selected application are extracted. Suppose `sendMessage()` is one of these methods. First, we applied preprocessing tasks to the `sendMessage()` method. Figure 5a illustrates the output of this step. Then, by using the pre-trained model from the second step, a summary was produced for the preprocessed running example (Figure 5b). From the nodes in the dynamic call graph that have outgoing edges to the selected node (method), we selected the node with the highest rank. We call this node a block. If the block has a corresponding method in the source code of the program, we use that source code as an input for the pre-trained model. Otherwise, the block is related to the Android framework. In this case, we create a dummy method by adding a signature to the block. For instance, in Figure 10, there is only one node called `onClick()`. Since `onClick()` is related to the Android framework, we created a dummy method for the `onClick()` element and passed it to the pre-trained model (Figure 5c). After adding the output of the latter step, the summary for the given method was generated (Figure 5d).

3 Evaluations

In this section, we present the results of both qualitative and quantitative evaluation of our proposed approach. First, the deep neural network was assessed using BLEU4 and METEOR metrics. Then, using an empirical study, we examined the usefulness of our approach in aiding developers comprehend event-driven programs. This qualitative assessment was performed on 14 Android applications.

3.1 Evaluations of Deep Neural Network

Here, we evaluate the deep neural network. We first present Research Questions (RQs), evaluation metrics and the evaluation process. Afterward, we discuss results of our evaluations and analyze them subsequently.
3.1.1 Research Questions
To evaluate our deep neural network, we answer the following four questions:

RQ1: How much the proposed model has been successful in learning comments/codes sets?
RQ2: What is precision of the generated summaries by the proposed model?
RQ3: What proportion of reference summaries where retrieved as the final generated summaries?
RQ4: How well has the proposed deep neural network performed regarding the other baseline deep neural networks?

3.1.2 Evaluation Metrics
Here, we investigate the evaluation metrics used in this study, namely BiLingual Evaluation Understudy (BLEU) and Metric for Evaluation of Translation with Explicit ORdering (METEOR).

BLEU is used for automated evaluation of machine translation algorithms [56]. Since code summarization is a type of translation of code snippets to human-readable summaries, BLEU can be used for evaluating abstractive code summarization. To understand how BLEU is computed, consider the following example. We have the below references for assessing the generated summaries. Reference summary is the correct or the real summary from our data set for a code snippet.

// Reference1: The statement creates the intent.
// Reference2: This statement creates the intent.

Furthermore, the generated summary is as follows: //Generated: the the the the the the.

For this example, the traditional precision metric is calculated as Precision = 5/5 = 1. Although the translation is definitely not good, precision’s value is at its maximum.

BLUE refines precision by valuing each term exactly for as many times as it has appeared in the reference translations. $P_1$ considers every term separately, so we have $P_1 = 5$ in the previous example. $P_2$ has a similar concept as $P_1$, except that it computes the precision of bigrams. Suppose, we have the following summary ($P_2$ is computed as $P_2 = \frac{1}{2+1}$):

//Generated: creates the creates the.

We compute the precision for different values of $n$ in n-grams. The final score is calculated using equation (11). In this equation, $BP$ is a penalty for short summaries, which are identified using equation (12). In equation (12), $r$ and $c$ are the lengths of reference and generated summaries, respectively.

$$\text{BLEU} = BP \times \exp \left( \sum_{i=1}^{N} \frac{\log(P_i)}{N} \right)$$  \hspace{1cm} (Eq. 11)

$$BP = \begin{cases} 1 & c > r \\ \exp \left( 1 - \frac{r}{c} \right) & c \leq r \end{cases}$$  \hspace{1cm} (Eq. 12)

METEOR was proposed to mitigate BLEU’s shortcomings [57]. METEOR focuses mainly on recall, unlike BLEU which pays more attention to precision. METEOR is based on the term-to-term mapping of the generated summary with its corresponding reference summary. Suppose the term activity has appeared once in the generated summary but twice in the reference summary. Therefore, it will be assigned to the reference term twice. To find the most suitable mapping, METEOR uses a heuristic. Mapping occurs at the following three cases. When two terms are exactly the same, when two terms have common stems, or when they are semantically similar.

METEOR is calculated using equation (13). In equation (13), $R$ is the refined recall, $P$ is the refined precision and $PN$ is the penalty (which is issued for having only unigrams).

$$\text{METEOR} = \frac{10RP}{R + P} \times (1 - PN)$$  \hspace{1cm} (Eq. 13)

In equation (14), $C$ is the number of common chunks between the generated and reference summaries.

$$PN = 0.5 \times \left( \frac{C}{M_u} \right)^3$$  \hspace{1cm} (Eq. 14)

To better understand chunks, consider the following example, which has two common chunks:
In cases that reference and generated summaries are identical, there is only one chunk. On the other hand, if there exists only unigrams, number of chunks equals to the number of term-to-term mappings, which is denoted as $M_u$. Therefore, METEOR can reduce $F_{\alpha=\frac{1}{2}} = \frac{10 R P}{R+P}$ to half.

### 3.1.3 Evaluations Setup

Our deep neural network uses Github as an input resource. Some of the pairs did not have enough comment length. Therefore, we removed pairs with comments shorter than four words. Furthermore, some of the comments are too long to be used for training deep neural networks. Yin et al. [58], claimed that most of the summaries are less than three sentences. Moreno et al. [10], stipulated that summaries with less than 20 terms are suitable for comment generation. Consequently, comments with more than 35 words were removed from the pairs. Similarly, source codes with more than 100 tokens were removed. Some of the comments neither were written in English nor were produced by human (They were generated automatically). Finally, by applying a few minor heuristics, we selected 71257 pairs of comment/code. Table 2 describes statistical information about these pairs.

| Mean | Q1 | Q2 | Q3 | # Unique tokens |
|------|----|----|----|-----------------|
| 11.25| 7  | 9  | 14 | 44934          |
| 33.49| 15 | 26 | 47 | 22525          |

### 3.1.4 Evaluations Results

To answer the RQ1, we used perplexity metric [59]. Perplexity estimates how well a deep neural network can perform on a training dataset. It is calculated using $\text{Perplexity} = \exp(\mathcal{L})$, in which $\mathcal{L}$ is the cross-entropy loss function. Table 3 shows best perplexity values in the 10 last epochs. Moreover, Figure 11 presents cross-entropy loss function based on different epochs.

![Cross-entropy loss values based on different epochs.](image)

To answer the RQ2, we used the BLEU4 metric. The maximum number of terms for generated summaries is 35, which is considered short. Therefore, based on the suggestion of Papineni, et al. [56], we used the maximum four-grams in
calculating the value of this metric. Table 3 illustrates BLEU4 results based on different parameters. BLEU4 for 200 epochs on our test dataset equaled to 30.91.

To answer the RQ3, we used METEOR metric. METEOR for 200 epochs on our test dataset equaled to 12.71. Table 3 presents the values of discussed metrics for different parameters.

Table 3: Results of the Proposed Deep Neural Network with Different Parameters

| Batch size | Beam width | # of layers | # of epochs | Pre-trained model | BLEU4 | METEOR | Perplexity |
|------------|------------|-------------|-------------|------------------|-------|---------|------------|
| 512        | 50         | 4           | 200         | ✓                | 30.77 | 11.25   | 3.53       |
| 512        | 50         | 4           | 200         |                  | 31.01 | 6.65    | 5.16       |
| 512        | 50         | 3           | 200         | ✓                | 30.69 | 11.84   | 1.95       |
| 512        | 50         | 2           | 200         | ✓                | 30.91 | 12.71   | 1.84       |

To answer the RQ4, we applied the baseline introduced by Iyer et al. [17]. Table 4 presents results of the proposed deep neural network’s performance in comparison with their approach. They generated summaries using RNNs and attention mechanism. Authors used an embedding layer, which they initialized randomly. Furthermore, they applied a beam search algorithm for generating summaries. They collected the data for their study from Stack Overflow, a well-known question and answering website (Q&A) [60]. Stack Overflow is the flagship site of the Stack Exchange Network website and is a platform for questions and answers in a wide range of software developing topics [60].

Table 4: Comparing Proposed Approach to the Baseline

| Method               | Language | METEOR | BLEU4 |
|----------------------|----------|--------|-------|
| CODE-NN [17]         | C#       | 12.3   | 20.5  |
| The proposed approach| C#       | 8.4    | 30.9  |
| CODE-NN [17]         | SQL      | 10.9   | 18.4  |
| The proposed approach| SQL      | 8.5    | 31.5  |

3.1.5 Quantitative Analysis of Results

According to Table 3, cross-entropy loss function has decreased 1.84 per word in perplexity. This indicates that the proposed model has efficiently performed on the training dataset. Furthermore, according to Figure 11, the model has not progressed significantly after for epoch number 170. Therefore, we believe increasing the epoch number to more than 200 does not improve the performance of the model very much.

Table 4 compares the proposed neural network with the baseline. According to results, our model has improved BLEU4 for both C# and SQL programming languages to the extent of more than 50%. However, baseline performed better regarding the METEOR metric. This is probably due to our model was originally designed for Java programming language and did not include any preprocessing on other languages such as SQL and C#. This is confirmed by Table 3 which presents results for Java. METEOR for Java increased to 12.71.

3.2 Evaluations of Generated Summaries

Here, we evaluate the usefulness of our model in aiding Android applications’ comprehension using an empirical study.

3.2.1 Research Questions

To evaluate generated summaries, we investigate the following questions:

**RQ1** Considering the reference summaries, how accurate have been the generated summaries?

**RQ2** How well has performed the proposed model regarding other approaches?
RQ3 How is the quality of the generated summaries?

3.2.2 Evaluations Setup

We used 14 Android applications with different sizes to evaluate the generated summaries. We selected these applications because they are open source and have been used in other researches as well [61,62]. Table 5 presents these applications.

Table 5: Set of Android Applications Used in the Empirical Study

| Application Name       | # of lines | # of Methods | # of Classes |
|------------------------|------------|--------------|--------------|
| Tister                 | 423        | 14           | 8            |
| Hashpass               | 429        | 8            | 2            |
| Munchlife              | 631        | 17           | 9            |
| justsit                | 849        | 43           | 13           |
| Blinkenlightsbattery   | 851        | 61           | 14           |
| Autoanswer             | 999        | 50           | 13           |
| Anycut                 | 1095       | 60           | 18           |
| Dofcalculator          | 1321       | 14           | 9            |
| Divideandconquer       | 1824       | 156          | 28           |
| Passwordmakerpro       | 2824       | 282          | 67           |
| Trippytipper           | 2953       | 148          | 36           |
| Tokenlist              | 3680       | 225          | 43           |
| Httpmon                | 4939       | 392          | 86           |
| Remember               | 5915       | 257          | 54           |

First, we randomly selected two methods from each application and wrote a summary for each one manually by carefully considering the context of those methods and interactions among elements. Afterward, a second summary was generated for each method using the proposed model. To be able to answer the RQ3, we had to know the opinions of practitioners about the generated summaries. Therefore, we designed an online questionnaire to qualitatively assess the results, and presented the above summaries to the participants to help them evaluate the generated summaries more efficiently. Our participants consisted of three groups: five Ph.D., 15 master, and six bachelor students majored in computer science, with an average of 6.4 years of general programming experience, 2.9 years of Java programming experience, and 1.3 years of Android programming experience. It took each participant on average 78 minutes to finish the questionnaire. We analyzed the generated summaries from two perspectives; their informativeness and naturalness [17].

Informativeness What proportion of the important parts of the code does the generated summary cover.

Naturalness How smooth and human-readable is the generated summary. Naturalness also takes into account the syntax of each sentence.

Participants scored the generated summaries for each method based on a 1-5 star scaling. Description of each score is as follows:

- **Informativeness:**
  - One star: the generated summary does not describe the method’s functionality to any extent.
  - Two stars: the generated summary documents some insignificant parts of the code and ignores the more important parts.
  - Three stars: some important parts of the code are neglected.
  - Four stars: most of important parts are covered in the summary.
  - Five stars: all significant and essential parts of the code are well documented.

- **Naturalness:**
  - One star: the generated summary is not readable for humans.
  - Two stars: the generated summary is understandable, but barely.
Three stars: the generated summary is understandable, but has noticeable syntax errors.
Four stars: the generated summary is understandable, but has small syntactical errors.
Five stars: the generated summary is understandable with no syntactical errors.

3.2.3 Evaluations Results

To answer the RQ1, we calculated BLUE4 and METEOR metrics for each method. The first author of this paper has developed the CrowdSummarizer tool [2]. Since the source code was available to us, we compared our new results to the mentioned approach to answer the RQ2. We selected BLEU4 and METEOR as our evaluation metrics. The model of CrowdSummarizer [2] was applied to the extracted methods in the previous question. Additionally, the sequence-to-sequence [43] model with the attention mechanism was implemented as another approach. Tables 6 presents the comparison results of these three approaches.

Table 6: Comparison of the Proposed Approach with the Existing Approaches

| Approach                        | METEOR | BLEU4 |
|---------------------------------|--------|-------|
| CrowdSummarizer [2]             | 12.44  | 28.16 |
| Sequence-to-sequence [43]       | 12.80  | 31.80 |
| The proposed approach           | 16.91  | 32.20 |

To answer the RQ3, Table 7 presents results of each participant in terms of informativeness and naturalness. The mean scores for informativeness and naturalness for all participants are 3.69 and 4.48, respectively.

Table 7: Participants’ Ratings for Informativeness and Naturalness

| Participant | Mean of informativeness | Mean of naturalness |
|-------------|-------------------------|---------------------|
| 1           | 4.15                    | 4.30                |
| 2           | 3.75                    | 4.65                |
| 3           | 4.35                    | 4.20                |
| 4           | 4.25                    | 4.50                |
| 5           | 3.65                    | 4.50                |
| 6           | 4.70                    | 4.95                |
| 7           | 3.65                    | 4.40                |
| 8           | 3.45                    | 4.75                |
| 9           | 3.60                    | 4.40                |
| 10          | 4.10                    | 4.60                |
| 11          | 4.50                    | 4.45                |
| 12          | 2.90                    | 4.75                |
| 13          | 4.40                    | 4.25                |
| 14          | 3.40                    | 4.70                |
| 15          | 3.35                    | 4.55                |
| 16          | 4.40                    | 4.65                |
| 17          | 3.75                    | 4.75                |
| 18          | 3.40                    | 4.50                |
| 19          | 3.40                    | 4.65                |
| 20          | 3.00                    | 4.75                |
| 21          | 4.00                    | 4.15                |
| 22          | 3.15                    | 4.55                |
| 23          | 2.60                    | 3.95                |
| 24          | 2.75                    | 4.30                |
| 25          | 3.40                    | 3.95                |
| 26          | 3.90                    | 4.45                |

Figure 12 depicts the distribution of informativeness and naturalness variables.
3.2.4 Quantitative Analysis of Results

According to Table 6, average BLEU4 and METEOR of the proposed approach are 32.20 and 16.91, respectively. Our proposed model has increased BLEU4 more than one percent and METEOR more than 30 percent.

Figure 13 depicts BLEU4 and METEOR distributions of the proposed and existing approaches. To investigate whether there is a significant difference between the results of our proposed approach and other existing approaches, we first calculated Cohen’s $d$ effect size [63]. The effect size is a measure to show the degree of difference between the two categories. Cohen stipulated that the value of $d \approx 0.2$, $d \approx 0.5$, and $d \approx 0.8$ respectively suggest small, medium, and large differences between the two categories. Sawilowsky [64] extends Cohen’s work and proposed a slightly different scale, that is $d \approx 0.1$, $d \approx 0.2$, and $d \approx 2$ respectively suggest very small, very large, and huge differences between the two categories. We also applied two-tailed Student’s t-test with a confidence level of 95% ($\alpha = 0.05$). We define the null and alternative hypotheses as follows:

$H_0$ There is no significant difference between the two categories.

$H_1$ There is a significant difference between the two categories.

The p-value of our proposed approach and Crowdsummarizer regarding BLEU4 and METEOR are about $10^{-10} < \alpha$ and $0.03 < \alpha$. Therefore, we reject the null hypothesis $H_0$, meaning there is a significant difference between the results of these two approaches. Additionally, Cohen’s d values are about 2.20 and 0.49 which indicate huge and medium effect sizes, respectively. The p-value of our proposed approach and sequence-to-sequence regarding BLEU4 and METEOR are about $0.22 > \alpha$ and $0.8 > \alpha$, which means we cannot reject the null hypothesis $H_0$. However, Cohen’s d values are 0.21 and 0.39 which means we have small and medium effect sizes, respectively.

According to Table 7, sample means for informativeness and naturalness are $\overline{X}_{\text{inf}} = 3.69$ and $\overline{X}_{\text{nat}} = 4.48$, respectively. We applied t-distribution to estimate mean and standard deviation of informativeness and naturalness results. Using equation (15), and the confidence level of 95% ($\alpha = 0.05$),

\[
\hat{\sigma}_{\overline{X}_{\text{inf}}} = \frac{s_{\text{inf}}}{\sqrt{N}} = 0.11
\]

\[
\hat{\sigma}_{\overline{X}_{\text{nat}}} = \frac{s_{\text{nat}}}{\sqrt{N}} = 0.05. \quad (\text{Eq. 15})
\]

We can compute equation (16),

\[
\mu = \overline{X} \pm t_{(N-1=25,\alpha=0.05)} \times \hat{\sigma}_{\overline{X}}. \quad (\text{Eq. 16})
\]
Therefore, we can conclude that

\[
\bar{\sigma}_{X_{\text{inf}}} = 3.69 \pm 0.23 \\
\bar{\sigma}_{X_{\text{nat}}} = 4.48 \pm 0.10.
\]  \hspace{1cm} (Eq. 17)

Equation (17) shows that with the confidence level of 95%, by increasing the number of participants, in the worst case the mean scores for informativeness and naturalness will be greater than 3.46 and 4.38, respectively.

3.2.5 Qualitative Analysis of Results

According to Figure 12, and our definition of informativeness and naturalness metrics, we conclude as follows:

1. Participants in 29.6 percent cases reported that generated summaries cover all essential parts of the codes.
2. Participants in 60.6 percent cases reported that in the worst case, generated summaries cover many salient features of the code.
3. Participants only in 17.3 percent cases reported that generated summaries are not related to the codes or document just trivial code snippets.
4. Participants in 39.4 percent cases reported that generated summaries have neglected a few necessary parts of the codes.
5. Participants in 62.9 percent cases reported that generated summaries are human-readable and do not have any syntactical error.
6. Participants in 89.2 percent cases reported that in the worst case, the generated summaries have minor syntactical errors.
7. Participants in 10.8 percent cases reported that generated summaries are human-readable but have major syntactical errors.
8. Finally, participants only in 3.1 percent cases reported that generated summaries are barely human-readable.

4 Threats to Validity

In this section, we review threats to the validity of our research findings, categorizing possible threats into four groups of internal, external, construct and dependability ones [65].

4.1 Internal Validity

Internal validity asks whether the variables used in the proposed approach affect the outcomes and whether there are the only influential factors in the study [65].

The dynamic call graph in the Rundroid tool is constructed based on tests that are run on Android applications. These tests are run manually in the original version of the study [32]. Therefore, how the tests are run and their runtime
impact results. To reduce this threat, authors generated 5000 random events using the Monkey tool to minimize human intervention in the tests.

In the analysis section of our proposed approach, we evaluated the quality of final summaries extracted from 14 Android applications and 28 methods. It is reasonable that the quality of extracted methods affects results. To reduce this threat, we sampled randomly from extracted methods.

Twenty-six individuals performed our qualitative assessment. Therefore, the outcome of this section depends on characteristics of the individuals taking the questionnaire, such as their mood, the time it took them to fill the questionnaire, and other natural factors. To reduce this threat, we tried to have a large number of participants.

4.2 External Validity

External validity includes how expandable are results of a study, can they be used in other contexts, and do cause and effect relationships hold with other conditions as well [65].

In this study, we have used the Rundroid tool to build call graphs. The Rundroid is developed for generating call graphs in the Android framework. Therefore, it is not suitable for usage in other event-driven programs. To reduce this threat, we plan to investigate and use other tools in near future.

As mentioned above, 26 individuals performed our qualitative assessment of the generated summaries for the selected real-world Android applications’ methods. Because the number of participants is limited, we cannot extend our results to the rest of the developers’ community. To reduce this threat, we have tried to select a well-distributed sample of developers to assist in the evaluation phase.

In the first and second phase of the proposed approach, we have used deep neural networks. The deep neural network architecture can be employed in other contexts, namely other natural language processing fields.

Moreover, in the evaluation phase, we have only used the Android framework’s examples as event-driven programs. Thus, it is not guaranteed that our approach will perform the same on other event-driven programs such as web-based programs. In future, we plan to address this threat by evaluating our model on other event-driven platforms.

4.3 Construct Validity

Construct validity includes theoretical concepts and discussions of the experiment and the use of appropriate evaluation metrics [65].

Theoretical concepts used in this work, have been already evaluated and proved by the academic society. The proposed approach is a combination of different methods in a new context. We have evaluated the generated summaries not only by valid and reliable quantitative metrics but also through human qualitative judgment. Results indicate that the employed approach has been successful in generating summaries.

4.4 Dependability

Dependability validity answers to questions such as whether the findings are compatible, and whether the experiment and its results are reproducible [65].

Compatibility We evaluated the final generated summaries quantitatively and qualitatively. As shown in previous sections, their outcomes are compatible.

Reproducibility we have used deep neural networks (which are inherently based on probability) to generate the summaries of event-driven programs’ methods. To reduce this threat, we have set the number of epochs to 200. This is because cross-entropy loss function is almost stable after the 170th epoch and did not decrease in our experiments. Also, the preprocessed input data is available online for other researchers at https://github.com/ase-sharif/deep-code-document-pairs. It is worth mentioning that we have tried our best to minimize human intervention in all steps to make results more independent and reliable.

5 Related Work

In this section, we review three previous types of approaches to code summarization, namely information retrieval, machine learning, and crowdsourcing. According to Table 8, most of these approaches have exploited machine learning techniques. Among these techniques, topic modeling is a popular one. However, in recent years, neural networks have been used as a new path to source code summarization. More than 90 percent and about half of the existing approaches,
summarize methods and classes, respectively. As for evaluation, BLEU4 and METEOR has been recently favored over precision and recall measures. The Java programming language is the most popular language used in source code summarization techniques. We present an overview of these approaches in the following.

5.1 Code Summarization via Information Retrieval

Information Retrieval is the process of extracting intended information from a document [66]. Sridhara et al. [8], proposed an algorithm for automatic description of Java methods. They applied preprocessing on Java methods using the Software Word Usage Model (SWUM). SWUM is a technique for displaying methods of a program in the form of noun, verb, and adverb groups.

McBurney et al. [20], introduced an approach for the automatic generation of documents for Java methods based on the context. Context not only can specify tasks of a method but also it can help understand why that method exists in the first place. Their approach is based on the PageRank [54], SWUM [8], and Natural language generation system [67]. In summary, this approach uses PageRank to find the most important methods for the given context. SWUM helps determine what these most important methods do. Finally, natural language generation system generates a human-readable summary.

Rodeghero et al. [19] proposed a method for choosing essential words of a code segment. They analyzed developers’ eye-movements and their focused attention while writing summaries for a method, and then used their findings to weight the words subsequently. Ten developers in an 1-hour session separately read 67 Java methods, then comprehended and finally summarized them. They identified and weighted words with the most attention through analyzing results of the above experiment.

Antoniol et al. [9] proposed an approach for improving traceability links between a code segment and its document. They utilized the unigram language model and Vector Space Model (VSM). Unigram language model was used to link a code and a document, and VSM to present each document as a vector of words. If a word appears in a document, a non-zero value is saved for it in its corresponding place in the vector. VSM does not restrict how one can compute these values. In this work, they presented documents and codes as a VSM. Then used cosine similarity to find traceability links between code and document.

Moreno et al. [10], presented an approach for summarizing Java classes. They primarily focused on each class content and tasks but did not heed the connection between classes. They first found a class’s stereotypes and its methods. Then classified stereotypes into 13 groups. Afterward, using natural language rules, they generated a summary for each class based on a specific format. In the end, the authors built a tool for automatic class summary generation [68]. They extracted 166 code snippets along with their description from Google Android Guide [69] in which 52 were sampled randomly. They asked 16 developers to write a summary of these code snippets. They collected 156 summaries. Analyzing these summaries, they discovered that none of the developers used the words in code segments in their summaries of code snippets, meaning abstractive summaries are more suitable comparing to extractive summaries.
5.2 Code Summarization via Machine Learning

McBurney et al. [11], presented a code summarization method using hierarchical topic modeling. Topic modeling is a statistical model used for extracting groups of words (topics) from a collection of documents [11]. They applied the Hierarchical Document Topic Model (HDTM) algorithm to their data [70]. The most abstract description of program’s tasks is given in the highest level of the hierarchy. As one goes down the hierarchy, descriptions become more precise and clear. Authors first formed the call graph with methods as nodes and caller callee among methods as edges of the graph. Then, HDTM was performed on the graph.

Haiduc et al. [12], considered code as text and exploited previous text summarization methods for summarizing code snippets as well. They used the VSM and Latent Semantic Indexing (LSI) [71] in their work. Authors first considered each method as a document, and then calculated cosine similarity between word vectors and their selected document for summarization. Next, they sorted the words based on their similarity scores and selected k most similar words for the given document. LSI then uses this k-word list for generating a high-level summary of the whole program. Eddy et al. [15], proposed a code summarization algorithm using hierarchical topic modeling. In fact, this study is a replica of the Haiduc et al. work [12], with the distinction that they utilized HPAM instead of VSM and LSI.

Programming tools help developers hide or reveal some parts of their code. This feature is known as code folding. Fowkes et al. [14], introduced an approach for code summarization through code folding. They summarized code using code. First, they formed an Abstract Syntax Tree (AST) of a code segment. Then they built the foldable tree through labeling block types and line numbers. Finally, they identified nodes that should be hidden using the extended version of Latent Dirichlet Allocation (LDA) algorithm [72] and sub-tree optimization.

Recently, researchers have been using neural networks as a method for generation summaries. Allamanis et al. [16], introduced a novel attention mechanism using Convolutional Neural Networks (CNN) [73]. Their goal was to generate the name of a method from its code.

Hu et al. [18], produced descriptions for Java methods using a sequence-to-sequence model. They applied a neural network for training open-source projects on Github. To improve performance, they exploited the structured form of code and introduced a novel method to parse abstract syntax tree. Then they used the parsed abstract syntax tree as an input for the neural network.

5.3 Code Summarization via CrowdSourcing

Badihi et al. [2], proposed a code summarization for Java language using the power of crowdsourcing. They built a web-based system for developers and encouraged them to write summaries for various methods using gamification techniques. Then they collected these summaries and analyzed them to identify the most significant parts of methods from developers’ point of view. In other words, they computed corresponding weights for different code snippets. For summarizing Java methods, they extracted essential words by using TF-IDF, and considering the exact place of the name of a method from its code.

Fowkes et al. [14], introduced an approach for code summarization through code folding. They summarized code using code. First, they formed an Abstract Syntax Tree (AST) of a code segment. Then they built the foldable tree through labeling block types and line numbers. Finally, they identified nodes that should be hidden using the extended version of Latent Dirichlet Allocation (LDA) algorithm [72] and sub-tree optimization.

Nazar et al. [4], presented a code by code summarization approach using crowdsource knowledge and supervised learning. First, they extracted code snippets from the most frequently asked questions (FAQ) section of Integrated Development Environment (IDE). Then they used four developers for labeling these code segments. Each line of code is labeled as a “yes” or “no”; “yes” means use the line in summary and “no” means do not. Afterward, if there were more than one “yes” label for a line, they would use it in the summary. Next, they extracted code features using crowdsourcing. For instance, method call, initializing and defining a variable are features of the code. In all, they extracted 21 features. Then, they utilized Support Vector Machine (SVM) and Naïve Bayes algorithms to classify results, and finally generated summaries using these two supervised learning algorithms.

Guerrouj et al. [5], used the context available in posts of Stack Overflow Q&A website in order to generate code summaries. Using an Island parser, they extracted identifiers from discussions about an element. This was done using an Island parser. They utilized term proximity to find context of identifiers and generated summaries based on the language model.

Rahman et al. [6], proposed an approach to generate summaries to recommend to developers through analyzing discussions and comments of users on Stack Overflow posts. First, they crawled questions and answers along with their comments from the website. Then separated the code snippets from the texts in the data and analyzed part of this data as the training dataset. Then, they formed a graph based on comments linking to their previous and next comments. If a person were mentioned in a comment, there would be an edge between the two corresponding nodes in the graph. They performed the page rank algorithm on the constructed graph. They also applied sentiment analysis on the comments.
and excluded comments with positive sentiment. In the end, they recommended the top three comments based on their scores as possible summaries code snippets.

Wong et al. [7], introduced a method for automatic documentation of codes using Github. They first crawled 1005 number of source codes of open source projects from Github. Then, using clone detection techniques, they extracted code snippets similar to the input code. Authors used a heuristic to exclude some of the extracted clones. Two groups of code clones were omitted; firstly code snippets that did not contain any method call and secondly clones that contained repetitive commands such as variable initializing. Next, they extracted documentations of the remained code snippets, sorted the documentation based on their text similarity with code snippets and finally summarized them.

As reviewed above, there are many approaches to code summarization. However, they have their limitations. One major defect of existing solutions is that to the best of our knowledge they do not consider dynamic interactions among elements of a software program. As interactions are triggered at run-time, they cannot be inferred statically. Therefore, to exploit this information to generate better summaries for code snippets, one needs to investigate these codes at run-time. In this work, we utilize these valuable interactions to generate more useful summaries.

Another frequent shortcoming of the existing approaches is related to their evaluations. Most of the current models are evaluated using the precision and recall metrics. As shown in Section 3, these metrics lack the validity for evaluating machine translations tasks. That is why we have used BLEU and METEOR to better evaluate the performance of our proposed model.

Moreover, most of these approaches are template-based, that is they generate summaries based on predefined rules. Therefore, these summaries neglect the essential semantics of a task/code, which renders them not very useful for end users in real-world cases. In this work, we have used deep learning methods to overcome this issue and generate more meaningful summaries.

6 Conclusions and Future Work

Code summarization is a useful technique for helping developers comprehend and maintain software programs more efficiently. There are different approaches for summarizing code segments, namely utilizing information retrieval, machine learning, and crowdsourcing knowledge. However, existing approaches do not take into account the interactions between different parts of the code while the program is running. Through exploiting deep neural networks and dynamic generation of the call graph, we tried to overcome the deficiencies of previous work and generate summaries that are more suitable. Results of the proposed approach were evaluated both qualitatively and quantitatively. We used BLEU4 and METEOR metrics for quantitative assessment and an online questionnaire for assessing the informativeness and naturalness of generated summaries in developers’ perspectives as means of qualitative assessment. Our results indicate that the proposed approach outperforms state-of-the-art techniques.

As for future work, one of the conventional solutions while using the sequence-to-sequence models is to employ a convolutional layer in the encoding component [74]. Adding this layer helps the deep neural network attain additional information about the words around each word. The use of a convolutional layer has improved results in machine translation studies. We intend to exploit this layer in future and analyze its effect on the proposed model.

Moreover, the Android framework is only one example of event-driven applications. In the future, we are going to examine other frameworks to evaluate the proposed approach and expand our findings.

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