HatCUP: Hybrid Analysis and Attention based Just-In-Time Comment Updating

Hongquan Zhu
State Key Lab for Novel Software Technology, Nanjing University
Nanjing, China
hqzhu@smail.nju.edu.cn

Xincheng He
State Key Lab for Novel Software Technology, Nanjing University
Nanjing, China
xinchenghe2016@gmail.com

Lei Xu∗
State Key Lab for Novel Software Technology, Nanjing University
Nanjing, China
xlei@nju.edu.cn

ABSTRACT
When changing code, developers sometimes neglect updating the related comments, bringing inconsistent or outdated comments. These comments increase the cost of program understanding and greatly reduce software maintainability. Researchers have put forward some solutions, such as CUP and HEBCUP, which update comments efficiently for simple code changes (i.e. modifying of a single token), but not good enough for complex ones. In this paper, we propose an approach named HatCUP (Hybrid Analysis and Attention based Comment UPdater), to provide a new mechanism for comment updating task. HatCUP pays attention to hybrid analysis and information. First, HatCUP considers the code structure change information and introduces a structure-guided attention mechanism combined with code change graph analysis and optimistic data flow dependency analysis. With a generally popular RNN-based encoder-decoder architecture, HatCUP takes the action of the code edits, the syntax, semantics and structure code changes, and old comments as inputs and generates a structural representation of the changes in the current code snippet. Furthermore, instead of directly generating new comments, HatCUP proposes a new edit or non-edit mechanism to mimic human editing behavior, by generating a sequence of edit actions and constructing a modified RNN model to integrate newly developed components. Evaluation on a popular dataset demonstrates that HatCUP outperforms the state-of-the-art deep learning-based approaches (CUP) by 53.8% for accuracy, 31.3% for recall and 14.3% for METEOR of the original metrics. Compared with the heuristic-based approach HEBCUP, HatCUP also shows better overall performance.

1 INTRODUCTION
As the complexity of software projects and the frequency of software product iterations continue to increase, program comprehension is becoming more important throughout the software development process. As recently shown by Xia et al. [47], 58% of developers’ time was spent in comprehending code. In addition to the code itself, code comments are considered as the most important form of documentation for program comprehension [3]. Source code is constantly evolving, with developers regularly refactoring and integrating new functionality; however, code comments are often ignored when the code goes through changes [32, 37, 45], leading to the inconsistency between code and comments that not only brings about confusion in software development and maintenance [15] but can also result in bugs [37].

Comment generation aims to summarize code snippets with code representations [1, 15, 23, 42, 51] by generating an entirely new comment related to the current version of the code. However, they cannot retain some content intended to be highlighted in the existing comment. Recently, some approaches have been proposed to focus on automatic comment updating. For example, Liu et al. [26, 28] propose a just-in-time technique, called CUP, to cope with the problem of the widespread presence of inconsistent comments. The core idea of CUP is to leverage a neural sequence-to-sequence model to learn comment update patterns from old comments and changed code tokens.

Although CUP has good performance on comment updating, it has some limitations. Lin et al. [24] find that since major correct comments generated are related to modifying a single token, CUP tends to fail when its actual application scope is limited due to frequent updates. Hence, Lin et al. propose a heuristic-based comment updater HEBCUP that has the edge over CUP by focusing on the changed code patterns. However, HEBCUP also lacks efficiency faced with processing complex updating. When there are many changed code tokens or the code changes are not directly related to the old comment, CUP and HEBCUP may fail to make correct updates.
This paper proposes a new approach called HatCUP to address comment updating in complex scenarios. Firstly, HatCUP considers more about the code structure change information. Instead of only focusing on code text changes, HatCUP pays attention to hybrid analysis and information with a structure-guided attention mechanism. It proposes a constraint-based optimistic data flow dependency analysis. Specifically, the derivation of such data-flow is not through conservative standard data-flow analysis, but rather similar to how humans derive data-flow, and more effective to the comment updating scenario. Combined with constraint-based optimistic data flow dependency analysis and code change graph analysis, HatCUP can obtain the changed variable nodes and their associated dependencies on each other. Then, HatCUP constructs a change-guided and dependency-guided attention mechanism to help the model focus on changed syntax nodes and long-term dependencies among variables. Hence, HatCUP can collect complete information even when the code changes are not directly related to the old comment.

Secondly, with the core idea of imitating human editing behaviors, HatCUP considers more about edit actions (e.g., inserting, deleting and updating) on original comments instead of directly generating new comments. HatCUP modifies an RNN-based encoder-decoder model that is shown to be effective for many Software Engineering (SE) tasks [15, 27, 40] to integrate our newly developed component. Based on the model, HatCUP proposes a new edit or non-edit mechanism to emphasize the possibility that a certain token in the old comment will be edited to match the new code patterns. Specifically, the edit or non-edit mechanism leverages three different encoders to encode code changes, syntax changes and old comments. Then, HatCUP determines how the source code changes associated with the current decoding step changing the relevant parts of the old comment with three scenarios: (1) it decides whether a new edit action should be executed by generating an action-start keyword; (2) it preserves the current edit action by generating a common token; and (3) it suspends the current action until generating an action-end keyword. Finally, the decoder produces a series of edit actions, and HatCUP generates an updated comment based on the old comment and the corresponding edit actions.

To evaluate our approach, we use the same dataset in previous work [24, 28], which contains code-comment co-change samples extracted from 1496 popular engineered Java projects hosted on GitHub.

In summary, the contributions of this paper include:

- **Hybrid analysis and attention**: We consider the code structure change information and introduce a structure-guided attention mechanism combined with code change graph analysis and optimistic data flow dependency analysis. Based on the multiple information about code changes (e.g., the action of the code edits, the syntax, semantics and structure code changes, and old comments), a structural representation of the changes in the current code snippet can be generated.

- **A new mechanism for comment updating**: We propose a new mechanism, called edit or non-edit mechanism. Instead of directly generating a new comment sentence from scratch, the edit or non-edit mechanism generates a sequence of edit actions and constructs a modified RNN model to integrate newly developed component to mimic human editing behavior.

### Better performance

HatCUP is shown to outperform the two state-of-the-art techniques and can reduce developers’ efforts in updating comments. The results show that HatCUP outperforms CUP by 53.8% for accuracy, 31.3% for recall and 14.3% for METEOR of the original metrics. Compared with HEBCUP, HatCUP also shows better overall performance.

### Open Source

We open source the replication package of our work, including the dataset, the source code of HatCUP, our trained model and test results. All data in the study are publicly available at GitHub.

The rest of this paper is organized as follows: the motivating example is presented in Section 2. The technical details of HatCUP are described in Section 3. The evaluation for our approach is shown in Section 4. Section 5 discusses the situations where our approach may fail and the threats to validity. Related work and conclusions are in Section 6 and Section 7.

### 2 Motivation

Some comment updating approaches based on neural model learning and heuristic rules are not sufficiently effective beyond simple updates [24]. We take CUP [26, 28] and HEBCUP [24] as examples to demonstrate these limitations.

Figure 1 shows an example of stale comments we found in a real-world GitHub repository, Jitsi. In an earlier version, a project developer added a judgment condition (lines 2-3) in the method `parse()` to check if the variable `text` is `null`. However, the developer forgot to update the comment associated with this method, leading to a case of inconsistent comment. Fortunately, a developer found this problem and updated the comment later.

To realize the goal of updating automatically, CUP leverages a neural sequence-to-sequence model to learn comment update patterns from old comments and changed code tokens, and generates a new comment "returns the null text". However, since the return value of the target API `parse()` has another value assignment related to the variable `builder` in line 6 and the variable `text` in lines 1-4, which is not included in the changed token sequence, the information of structure and data flow dependency in code is ignored. CUP only gives comments about `null` and lacks the description "processed message" related to the original return value in line 6.

As a heuristic-based approach, HEBCUP applies updates of the code (sub)tokens to the corresponding comment (sub)tokens by matching the (sub)token in the old comment with the (sub)token in the old code one by one. For instance, if a method name is changed from "getX" to "getY", its comment may be updated from "return x" to "return Y". Its obvious disadvantage is that if the tokens of the code change do not match any tokens of the old comment, no updates can be made. Therefore, as shown in Figure 1, HEBCUP could not add the new return value "null" to the comment.

We propose HatCUP to provide a new mechanism for comment updating. In addition to the token sequences of code change and old comment, HatCUP considers more about the code structure change.

---

1 https://github.com/HATCUP0/hatcup
Motivating Example: jitsi/jitsi (stars: 3.5k)
Commit Id: c868e95

```java
public static String parse(String text) {
    if (text == null)
        return null;
    StringBuilder builder = new StringBuilder(text);
    ... return builder.toString();
}
```

Old Comment: returns the processed message
New Comment: returns the processed message or null if text message was null

| CUP | returns the null text |
|-----|-----------------------|
| HEBCUP | returns the processed message |
| HatCUP | returns the processed message or null |

Ground Truth
returns the processed message or null if text message was null

```
<UPDATE>
<UPDATEFROM> message or null if text message was null </UPDATEFROM>
<UPDATETO> [old tokens] 
</UPDATETO> [new tokens]
</UPDATE>
```

Figure 1: Motivating Example

3 APPROACH

Our approach, HatCUP, consists of three phases: edit representation, model training, and comment updating. Specifically, for each code-comment co-change sample extracted from source code repositories, we first represent them as edit sequences. Then, our model is trained using the preprocessed data. Finally, given code edits, syntax changes and associated the old comment, the trained model can automatically update the old comment to a new comment. In this section, we elaborate on the steps of our approach.

3.1 Representing Edits

In this phase, we convert code changes and comments into sequences. Different from CUP [28], we adopt a new representation of code and comment changes. We will describe it in detail in 3.1.2.

3.1.1 Data Pre-Processing. In the preprocessing, each code snippet is split into tokens, and each identifier is tokenized based on camel casing and snake casing. For comments, HTML tags and comment symbols(e.g., "/*" and "/") are all filtered out. Then, each string will be tokenized by space. After that, compound words, which are the tokens constructed by concatenating multiple vocabulary words according to camel or snake conventions, are split into multiple tokens to reduce OOV (Out Of Vocabulary) words.

3.1.2 Text Change Representation of Code and Comment. After tokenization, the old and new code snippets are converted to two token sequences separately. We use difflib\(^2\) to extract code edits. The code token sequence pair consists of a series of edit actions, which means editing an old code snippet to the new one. We construct each edit action as `<Action> [tokens] </Action>`, which has proven to be highly effective in other tasks in preliminary experiments [33]. We define four types of editing actions in our work: INSERT, DEL, UPDATE and KEEP. Notably, UPDATE action must incorporate content both before and after the update, thus explicitly indicating which tokens in the old comment are to be replaced with the new tokens, so it has a slightly different structure:

```
<UPDATEFROM> message or null if text message was null </UPDATEFROM>
<UPDATETO> [old tokens] 
</UPDATETO> [new tokens]
</UPDATE>
```

Especially, the comment edit representation is slightly different from the code representation. During inference, we only need to know the position and information of the changes made to the old comment. Therefore, we do not consider KEEP type when building the sequence of edit actions, since we can copy tokens that are retained between the old and new comments, instead of generating them anew. For DEL and UPDATE, we can remove or replace exactly the corresponding content from the old comment. For INSERT action, we design a method to determine which position of the old comment should be edited. Considering the example in Figure 1, the raw sequence `"<INSERT> or null if text message was null </INSERT>"` does not contain information about where the new string should be inserted. Therefore, we select the minimum number of tokens before the insert position as a tag, so the place of insertion can be uniquely identified. Consequently, we will generate the edit action: `<INSERTTAG> message or null if text message was null </INSERTTAG>`. Similar to the process of UPDATE, this sequence indicates that "message" should be replaced with "message or null if text message was null," effectively inserting "or null if text message was null" into the old comment.

\(^2\)https://docs.python.org/3/library/difflib.html
### 3.1.3 Syntax Change Representation

AST (Abstract Syntax Tree) provides crucial structure information for code understanding [10]. Given a pair of old source code $C_1$ and new source code $C_2$, we can obtain syntax change information with GumTreeDiff [7]. Variable nodes in the syntax tree will be used as the input of the syntax change encoder. However, this is not enough to help the model obtain structural information. We introduce a new attention mechanism for the comment updating scenario, the structure-guided attention shown in Figure 2.

In Figure 2, a code change graph is created by analyzing the syntax change information provided by GumTreeDiff. Each node in this graph is a triple tuple $\langle i, j, \langle\text{Operation}, \text{Type}, \text{Value}\rangle\rangle$. Operation means the edit operation of a node from $C_1$ to $C_2$, namely: keep, insert, del, update; Type is the syntax type of a node, such as “SimpleName”, “IStatement”, “Assignment” and so on; Value is the value of a node (if the node has).

To efficiently generate comment fragments for modified parts of the code, we propose change-guided attention. It focuses on the variable nodes in the code change graph involved in the change and their associated nodes. More formally, we introduce the following change-guided attention matrix:

$$M_{ij} = \begin{cases} 0 & \text{if } \{n_i, n_j\} \in A \text{ and } n_i/n_j \in CN \\ \text{-inf} & \text{otherwise} \end{cases}$$

(A is the set of node pairs $\langle n_i, n_j \rangle$, in which $n_i$ and $n_j$ are the same node (i.e., $i = j$) or nodes of the same value, or there is an assignment relationship between them. CN means the changed nodes set. After this attention matrix is passed to the softmax logical regression, all the parts set to -inf will be ignored in the subsequent calculations. Consequently, the change-guided attention is designed to block out information other than changes.

We also constructed the data flow dependency graph. On the one hand, the data flow contains semantic code information, which is crucial for code understanding. On the other hand, the data flow supports the model in considering long-term dependencies induced by using the same variables in distant locations. For example, there are six variables with the same name (i.e., $\min^1$, $\min^8$, $\min^{10}$, $\min^{12}$, $\min^{14}$ and $\min^{16}$) but different semantics in the data flow dependency graph in Figure 2. The graph demonstrates dependencies between variables and supports $\min^{16}$ in paying more attention to $\min^8$, $\min^{10}$ and $\min^{14}$ instead of $\min^4$.

We determine the data flow dependencies based on each variable object’s Output-flow and Input-flow. Inspired by PyART [14], we define a set of constraint-based optimistic data flow dependency extraction rules according to the target of our task. Such data flow is neither sound nor complete, and it just appears to be concise and largely precise, thus facilitating our incorporation of this information in the model. As shown in Table 1, we have summarized 11 output or input-flow patterns, including: $\text{MethodName}$, $\text{PostfixExpression}$, $\text{Assignment(left-hand)}$, $\text{PrefixExpression}$, $\text{InfixExpression}$, $\text{PostfixExpression}$, $\text{ContainerAccess}$, $\text{MethodInvocation}$, $\text{ReturnStatement}$ and $\text{Assignment(right-hand)}$ rules. We filtered out some patterns defined as Preservation, because they are not common and therefore cannot provide enough data to support the learning of the model (and hence should be killed). We construct data flow dependencies from $\text{OUT}(M)$ collection to $\text{IN}(M)$ collection. For each variable $v$ in $\text{IN}(M)$, there must be a flow from the nearest variable $v$ in $\text{OUT}(M)$ before it. Taking the method in Figure 2
as an example, $a^5$ (in $a > b$, InfixExpression) belongs to IN($M$), the nearest $a \in \text{OUT}(M)$ before $a^5$ is $a^4$ (in compare(int, $a$, ..), MethodParameter). Consequently, there is a data flow from $a^4$ to $a^5$. In addition, there must be a flow from the right-hand operand to the left-hand operand in an Assignment expression.

To represent the dependency relationship, we take a direct edge $e = \langle n_i, n_j \rangle$ from $n_i$ to $n_j$, which means that the value of the $j$-th node comes from the $i$-th node. The following dependency-guided attention matrix represents the dependency relationship:

$$M_{ij} = \begin{cases} 1 & \text{if } \langle n_i, n_j \rangle \in E \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

$E$ is the set of directed edges, $\{e_1, e_2, ..., e_n\}$. Similar to the change-guided attention matrix, the dependency-guided attention matrix will also be passed to the softmax logical regression; after calculation, the parts set to 1 will have a higher attention score than the parts set to 0, which means that the model will pay more attention to the dependency relationship among the variables.

Finally, we compute the weighted sum of change-guided attention and relation-guided attention matrices to obtain the final structure-guided attention matrix. We filter the variable nodes associated with the change for the task of comment updating and try to preserve the dependencies among the nodes. In summary, we do not serialize the traversal of AST nodes as previous work and input the flattened sequence, which results in corrupted structural information.

### 3.3 Encoders

After extracting as features the sequences of sub-tokens and nodes for the codes, we need to convert those sequences into vector representations for the models in the later steps. In detail, HatCUP leverages three different encoders, to encode code edit sequences, syntax change sequences and old comments, respectively. We use multiple GRUs for the different structures and types of information. Multiple GRUs also help reduce the cross-influence between different contexts.

#### 3.3.1 Token Embedding Layer

This layer is designed to map the various tokens, i.e., code tokens, comment tokens, edit action tokens and variable node tokens, into embeddings. We first created a vocabulary separately for code, variable nodes and comments. We choose to train the embedding layers from scratch instead of using a pretrained model, since the pretrained model may not contain some tokens, which will result in low effectiveness. Especially, for syntax change, we put the values of variable nodes as tokens into the encoder; as for old comments, we input only the split subtokens.

#### 3.3.2 Feature Fusing Layer

After the initial embedding of the tokens, we select extra features for each token, which has proven to be effective in learning associations between source code entities and comments [30]. These features are represented as one-hot vectors and are concatenated to code edit token embeddings or comment token embeddings.

For code edit sequences, which contain edit keywords, Java keywords, operators, variable names, etc., we need to make the model distinguish these tokens. If a token is not an edit keyword, we have indicator features for whether it is part of an INSERT, DEL, UPDATEFROM, UPDATETO, or KEEP span. These features are particularly helpful for longer spans, as the edit keyword only appears at the beginning or end of the span. In addition, the tokens in return statements usually appear in comments, and we introduce these features to guide the model in identifying relevant tokens in the code edits sequence and the old comment sequence.

For syntax change, we also have indicator features such as that in code edits tokens, telling the model which operation a node belongs to, i.e., keep, insert, del, update. Additionally, we take Type into consideration. According to a large-scale empirical study conducted...
by Wen et al. [45], change types Variable Declaration and Selection are among those more likely to trigger comment updates, at the method and class level. These changes could severely impact the application logic (selection) or the data manipulated in the code Variable Declaration.

Regarding old comments, we include whether a token matches an AST node that is insert, del, update in AST-diff. This treatment helps align parts of old comments with AST changes, helping the model determine where the edits should be made.

3.3.3 Modeling Layer. This layer produces the hidden states of each token based on its contextual vector. For each context, we encode it with a GRU. In our approach, the three GRUs share a similar structure.

As shown in Figure 3, the input for each GRU is the sequence $V$ of $n$ vectors representing a context. Each vector represents a sub-token combining other features. For example, one GRU is used to obtain the hidden states of code edits contextual vectors. For each time step $t$, we input one vector $V_t$ in these $n$ vectors, and the GRU returns one hidden state vector $h_t$ as the output for this time step. By collecting all outputs for each time step, we have a sequence of hidden state vectors $H = [h_1, h_2, ..., h_n]$, which is the output of the GRU. The whole procedure can be expressed by Formula 3. The other two GRUs share the same process.

$$h_t = f(v_t, h_{t-1}) \quad (3)$$

3.4 Attention Layer

In the modeling layer, we obtain the hidden states $H$ of the three GRUs separately. However, code edit, syntax change and old comment are represented independently. We cannot directly use them as input to the decoder to generate the result sequence. It is necessary to link and fuse their information to capture the relationships between different contexts. Therefore, we design three attention layers.

For each encoder, an attention layer is obtained by weighting and summing the outputs of all its timings. This attention layer contains information about the weight of each timing output, which is equivalent to identifying which text is important for the current token in the decoder. For instance, Code Edit Attention is used to identify the parts of the code relevant to the target edit sequence to be generated; Old Comment Attention is used to identify the notes needing to be edited in old comments. Syntax Change Encoder will be slightly different, and it uses the structure-guided attention we defined in Section 3.1.3.

For convenience, we take Code Edit Attention as an example. The attention layer takes as input the code edits contextual vectors, i.e., $H = [h_1, h_2, ..., h_n]$, and outputs an attention-aware contextual vector $C = [c_1, c_2, ..., c_n]$ for each edit token in Code Edits Attention. $c_t$ in $C$ is calculated as the weighted sum of the encoder’s hidden states:

$$c_t = \sum_{i=1}^{n} a_{ti} h_i \quad (4)$$

$$a_{ti} = \frac{e^{r(h'_{t-1}, h_i)}}{\sum_{r \neq i} e^{r(h'_{t-1}, h_r)}} \quad (5)$$

where $h'_{t-1}$ is the previous hidden state in the decoder, and $r$ is the function used to represent the strength for attention, approximated by a multi-layer neural network.

3.5 Decoder

By combining all the contextual vector outputs $C$ of all attention layers, we obtain a joint context; thus, the corresponding content from three input sequences is merged. We use a GRU as the decoder to generate a series of edit actions. At every decoding step, the
previous hidden state $h'_{t-1}$ is used as the input for the attention layer and the output of the attention layer will be used as the input of the GRU at time step $t$. Therefore, the resulting vector contains information related to the current decoder state together with knowledge aggregated from relevant parts of code edits, AST-diffs and old comments.

Different from the previous work, we do not generate a full new comment. Instead, we generate a series of edit actions to show how to update the old comment. Specifically, the decoder must determine how the source code changes associated with the current decoding step will change the relevant parts of the old comment. At each step, the decoder decides whether a new edit action should be executed by generating an action-start keyword from $\text{INSERT}$, $\text{DEL}$ or $\text{UPDATE}$ and continues the current edit action by generating a comment token; it will not stop the current action until an action-end keyword is generated. Since $\text{DEL}$ will include tokens in the old comment, and $\text{INSERT}$ tends to include tokens in the code, we add a pointer network to the decoder [41] to accommodate copying tokens from code and comment. The decoder generates a series of edit actions. Consequently, we can generate an updated comment by paring the old comment and the corresponding edit actions.

### Parsing Edit Sequences

Since the decoder gives us a series of edit actions, we should align it with the old comment and apply it to obtain the updated comment. We denote the old comment as $S_{\text{old}}$, the predicted edit actions as $S_{\text{edit}}$ and the corresponding parsed output as $S_{\text{new}}$. This procedure involves simultaneously following pointers, from left to right, on $S_{\text{old}}$ and $S_{\text{edit}}$, which we refer to as $P_{\text{old}}$ and $P_{\text{edit}}$ respectively. As $P_{\text{old}}$ moves forward, the current token is copied into $S_{\text{new}}$ at each point, until the pointer reaches an edit location. Then $P_{\text{edit}}$ applies the edit action of the current position, and the span tokens corresponding to the action are copied into $S_{\text{new}}$ if applicable. Finally, $P_{\text{edit}}$ moves to the next action; so do cases involving deletions and replacements; $P_{\text{old}}$ is also advanced to the appropriate position. This process will repeat until the two pointers reach the end of their respective sequences.

## 4 EVALUATION

### 4.1 Dataset

We use the same dataset in HEBCUP [24] and CUP [28]. The authors of the two works built a dataset from 1,496 Java projects hosted on GitHub and design rules to automatically filter out some types of syntactic optimizations (i.e., the old and new comments are of the same meaning) which may introduce bias. The cleaned dataset finally contains 80,591, 8,827, and 9,204 method-comment co-change samples for training, validation, and test sets, discarding 6,183 instances in total.

### 4.2 Research Questions

To evaluate HatCUP, we propose the following research questions.

- **RQ1:** How effective is HatCUP compared with the two state-of-the-art approaches, CUP and HEBCCUP?
- **RQ2:** How do the key components of HatCUP affect the result?
- **RQ3:** How effective is HatCUP when dealing with complex scenarios?

### 4.3 Experiment Setup

We conducted our experiment on Ubuntu 18.04.6 with Intel(R) Xeon(R) Gold 5118 CPU @ 2.30GHz. We utilized 1 NVIDIA Tesla V100 GPU to train and evaluate our model. The model was implemented in Python 3 with PyTorch V1.10.0. For our approach, 64-dimensional word embeddings are used for code edits tokens, AST-diff tokens and comment tokens. The hidden states of the Bi-GRUs (encoder) and the GRU (decoder) in our model are 64 and 128 dimensions respectively. All GRUs have two layers.

In our model, **Code Edit Encoder**, **Syntax Change Encoder**, **Old Comment Encoder** and the decoder are jointly trained to minimize the cross-entropy. During the training phase, we optimized the parameters of our model using Adam [20] with a batch size of 32. We set the learning rate of Adam to 0.001. A dropout [36] of 0.6 is used for dense layers before computing the final probability. The model with the best (smallest) validation perplexity is used for evaluation. A beam search of width 5 is used to generate the target sequence when testing.

### 4.4 Evaluation Metrics

We use **Accuracy**, **Recall@5**, **METEOR** [3], **SARI** [49], **GLUE** [29] and two metrics proposed by the authors of CUP [28] for this task, namely **Average Edit Distance (AED)** and **Relative Edit Distance (RED)**, to evaluate our approach and the baselines.

Our evaluation metrics are defined as follows:

- **Accuracy:** Accuracy represents the proportion of the test samples where correct comments are generated at Top-1 among the total number of cases examined. Here, correct comments refer to those that are identical to the ground-truth (i.e., written by developers).
- **Recall@5:** Similar to Accuracy, Recall@5 is the proportion of the test samples where correct comments are generated at Top-5.
- **AED:** AED measures the average word-level edit distance required to change the predicted results from CUP into the ground-truth. This value indicates the distance between the generated comments and the ground truth: the smaller, the better. The AED metric is defined as follows:

$$AED = \frac{1}{N} \sum_{k=1}^{N} edit\_distance\left(\hat{y}^{(k)}, y^{(k)}\right)$$

Where $N$ is the number of test samples, $edit\_distance$ is the word-level Levenshtein distance and $\hat{y}^{(k)}$ refers to the comment generated for the $k_{th}$ sample.

- **RED:** RED is similar to AED, but measures the average of relative edit distances. The RED metric is defined as follows:

$$RED = \frac{1}{N} \sum_{k=1}^{N} \frac{edit\_distance\left(\hat{x}^{(k)}, \hat{y}^{(k)}\right)}{edit\_distance\left(x^{(k)}, y^{(k)}\right)}$$

Where $x^{(k)}$ is the old comment for the $k_{th}$ sample. If an approach’s RED is less than 1, and developers can expect to spend less effort updating comments by using this approach.

- **METEOR:** METEOR (Metric for Evaluation of Translation with Explicit ORdering) is a metric for the evaluation of machine-translation output. The metric was designed to fix
4.5 Result Analysis

4.5.1 RQ1: The Effectiveness Evaluation. To evaluate the effectiveness of our proposed model, HatCUP, we evaluate it and the baseline methods on the testing set in terms of various metrics. The evaluation results for the dataset are shown in Table 2 and Table 3. From the tables, we can observe the following:

- HatCUP is slightly below HEBCUP by 5% in terms of the accuracy metric, and there may be several reasons. First, the ground-truth is rather subjective as a modified comment by the developer is not always consistent with the old comments. Since the old comment and the new comment are relatively simple modifications, it is not easy to guarantee that the modifications inferred by the model are consistent with the developer’s. Second, HEBCUP is a heuristic-based approach specifically designed for this scenario, which pays attention to the changed code and performs token-level comment updates. While for CUP, which is a deep learning-based work, i.e., CUP, has considered code changes and references between code changes and comments. Previous deep learning-based work, i.e., CUP, has considered code changes and references between code changes and comments. Therefore, we want to determine if the two key components would improve the task of comment updating. To this end, we compare HatCUP with its two variants: 1) HatCUP-syntax, which does not use the Syntax Change Encoder and the structure-guided attention mechanism, and 2) HatCUP-edit, which removes the edit or non-edit mechanism from HatCUP, generating the new comment directly instead of edit actions. The results are shown in Table 4. It can be seen that:

- HatCUP performs better than two variants in terms of accuracy. For accuracy, the improvements achieved by HatCUP range from 2.0% to 8.5%; for Recall@5, HatCUP improves by at least 4.2%, which means HatCUP can generate more correct comments than the variants. For AED and RED, HatCUP still achieves the lowest result. HatCUP minimizes the number of editing operations required for developers to update the old comments. HatCUP-edit achieves the worst performance. We manually inspected the test results to determine why the performance declined so much. Based on our inspection, we find that HatCUP-edit model tends to generate the same comments as the old comments. Since the old comment and the new comment are closely related, training a model to directly generate a new comment risks having it learn to just copy the old one.
- The introduction of the Syntax Change Encoder and the structure-guided attention mechanism improves the effectiveness of the model to a certain extent. From another point of view, even though HatCUP-syntax does not obtain the top results as HatCUP, it still achieves considerable performance

4.5.2 RQ2: The Effects of Key Components. The key of our comment updating task is to effectively capture the relationship and references between code changes and comments. Previous deep learning-based work, i.e., CUP, has considered code changes and references between code changes and comments. To better capture the potential code change information, we introduced a syntax change encoder together with the structure-guided attention mechanism. Additionally, we try to model the edit actions rather than generate comment sequences from scratch, defined as edit or non-edit mechanism. Therefore, we want to determine if the two key components would improve the task of comment updating. To this end, we compare HatCUP with its two variants: 1) HatCUP-syntax, which does not use the Syntax Change Encoder and the structure-guided attention mechanism, and 2) HatCUP-edit, which removes the edit or non-edit mechanism from HatCUP, generating the new comment directly instead of edit actions. The results are shown in Table 4. It can be seen that:

- HatCUP also outperforms the state-of-the-arts in terms of AED and RED. The AED metric drops from 3.52 to 3.44, which means for each comment, the developer can edit fewer words on average with HatCUP compared to the other tools. The lower RED metric also indicates that our approach can reduce the edits developers need to perform for just-in-time comment updating.
- Our model is better at editing comments, as shown by the results on METEOR, SARI, and GLEU in Table 3. The three metrics are flexible in word order and are often used to evaluate comment generation methods in prior studies.

In general, considerable improvements are achieved by HatCUP over CUP in terms of all metrics. Compared to HEBCUP, HatCUP performs much better on Recall@5 and outperforms it in AED and RED by substantial margins. This highlights that our approach can update comments more effectively and accurately than the baselines.

### Table 2: Comparisons of our approach with each baseline

| Approach | Accuracy | Recall@5 | AED   | RED   |
|----------|----------|----------|-------|-------|
| CUP      | 15.8%    | 26.8%    | 3.62  | 0.960 |
| HEBCUP   | 25.6%    | 27.6%    | 3.52  | 0.896 |
| HatCUP   | 24.3%    | 35.2%    | 3.44  | 0.861 |

### Table 3: METEOR, SARI and GLUE scores

| Approach | METEOR | SARI | GLUE |
|----------|--------|------|------|
| CUP      | 51.22  | 38.62| 50.30|
| HEBCUP   | 53.96  | 41.29| 54.14|
| HatCUP   | 58.52  | 45.63| 56.67|

* The scores are presented as percentage values between 0 and 100.

some of the problems found in the more popular BLEU metric and produce a good correlation with human judgment at the sentence or segment level.

- **SARI**: SARI is a metric used initially for evaluating automatic text simplification systems. The metric compares the predicted simplified sentences against the reference and the source sentences. It explicitly measures the goodness of words added, deleted and kept by the system.

- **GLEU**: GLEU metric is a variant of BLEU proposed for evaluating grammatical error corrections using n-gram overlap with a set of reference sentences, as opposed to precision or recall of specific annotated errors.

### 4.5 Result Analysis

#### 4.5.1 RQ1: The Effectiveness Evaluation. To evaluate the effectiveness of our proposed model, HatCUP, we evaluate it and the baseline methods on the testing set in terms of various metrics. The evaluation results for the dataset are shown in Table 2 and Table 3. From the tables, we can observe the following:

- HatCUP is slightly below HEBCUP by 5% in terms of the accuracy metric, and there may be several reasons. First, the ground-truth is rather subjective as a modified comment by the developer is not always consistent with the old comments. Since the old comment and the new comment are relatively simple modifications, it is not easy to guarantee that the modifications inferred by the model are consistent with the developer’s. Second, HEBCUP is a heuristic-based approach specifically designed for this scenario, which pays attention to the changed code and performs token-level comment updates. While for CUP, which is a deep learning-based work, i.e., CUP, has considered code changes and references between code changes and comments. Previous deep learning-based work, i.e., CUP, has considered code changes and references between code changes and comments. Therefore, we want to determine if the two key components would improve the task of comment updating. To this end, we compare HatCUP with its two variants: 1) HatCUP-syntax, which does not use the Syntax Change Encoder and the structure-guided attention mechanism, and 2) HatCUP-edit, which removes the edit or non-edit mechanism from HatCUP, generating the new comment directly instead of edit actions. The results are shown in Table 4. It can be seen that:

- HatCUP performs better than two variants in terms of all metrics. For accuracy, the improvements achieved by HatCUP range from 2.0% to 8.5%; for Recall@5, HatCUP improves by at least 4.2%, which means HatCUP can generate more correct comments than the variants. For AED and RED, HatCUP still achieves the lowest result. HatCUP minimizes the number of editing operations required for developers to update the old comments. HatCUP-edit achieves the worst performance. We manually inspected the test results to determine why the performance declined so much. Based on our inspection, we find that HatCUP-edit model tends to generate the same comments as the old comments. Since the old comment and the new comment are closely related, training a model to directly generate a new comment risks having it learn to just copy the old one.
- The introduction of the Syntax Change Encoder and the structure-guided attention mechanism improves the effectiveness of the model to a certain extent. From another point of view, even though HatCUP-syntax does not obtain the top results as HatCUP, it still achieves considerable performance
In conclusion, different from the two baselines, which use text analysis to capture change information, HatCUP takes structure code changes into account, which covers the shortage of baselines. In addition, updating comments through an edit mechanism rather than writing new comments from scratch also makes sense.

5 DISCUSSION
In this section, we discuss the situations where HatCUP may fail, and the threats to the validity of this work.

5.1 Where Does Our Approach Fail
Although our method has proven superior to existing methods, there are still scenarios where HatCUP does not perform perfectly. A common bad situation is that the code changes are too massive for HatCUP to handle perfectly. For example, the developer may rewrite the entire method, including the method name. In this case, the modified code can no longer be considered a variant of the original method. There is no connection between the old comment and the new code snippet. It is difficult for the model to update the old comment correctly by applying some edit actions.
Another situation, which we believe cannot simply be called a failure, is the optimization of language expression. For instance, the motivating example in Figure 1, whose comment was updated with a conditional clause ‘... if text message was null’, is a typical example of this situation. HatCUP may correctly update some of the comment phrases but not always all, which leads to inconsistency.

5.2 Threats to Validity

5.2.1 External Validity. A threat to external validity is related to GumTreeDiff we used to obtain the difference between ASTs. There is no guarantee that the syntax information extracted by GumTreeDiff is exactly correct. However, we manually checked 100 samples in the dataset and found only one incorrect mapping. Therefore, we believe the threat is limited.

5.2.2 Internal Validity. A threat to internal validity is related to the dataset we used. For comparison with CUP and HEBCUP, we directly used the dataset provided by them. The dataset is built only from Java projects and only contains updates of method comments, which may not be representative of all programming languages and comment types. Another threat is that the performance of HatCUP in solving complex cases is still not perfect. It needs more precise program analysis and efficient NLP algorithms.

6 RELATED WORK

In this section, we discuss related work concerning code-comment inconsistency detection, comment updating and comment generation. All these works focus on maintaining comments, but have different emphases.

6.1 Code-Comment Inconsistency Detection

A large amount of work has been conducted by researchers to detect inconsistent comments. Most prior works targeted comments related to specific code properties [37–39]. For instance, Tan et al. [37–39] proposed several approaches to detect the consistency between code and comment concerning specific code properties, such as lock mechanisms [37, 38], function calls [37] and interrupts [39]. They use static program analysis to check whether the source code conforms to specific rules. Some work has focused on specific types of comments [9, 18, 34]. For example, Huang et al. [18] used the text mining-based methods to predict whether a comment contains self-admitted technical debt (SATD) (e.g., TODO, FIXME, HACK). Sridhara [34] proposed a technique to identify obsolete TODO comments based on information retrieval, linguistics and semantics. Gao et al. [9] proposed a deep learning-based approach TDCleaner, which outperforms Sridhara’s by a large margin. Several studies focused on general comments. Ratol et al. [32] designed a rule-based approach named Fraco to detect fragile comments during identifier renaming. Panthapackel et al. [31] developed a deep learning-based approach for just-in-time code-comment inconsistency detection by learning to relate comments and code changes.

6.2 Comment Updating

Following the work of code-comment inconsistency detection, some approaches have been proposed to focus on automatic comment updating. Liu et al. [28] are the first to propose a just-in-time comment updating technique, called CUP. The core idea of CUP is to leverage a neural sequence-to-sequence model to learn comment update patterns from old comments and changed code tokens; then, it can update the comment in time after the developer modifies the code. Lin et al. [24] performed an in-depth analysis on the effectiveness of CUP. They found that most of the successful updating conducted by CUP was related to a single token change. Therefore, for the case of single token modification in the code, they proposed HEBCUP, a heuristic-based approach, which achieves better performance on CUP. However, HEBCUP is not sufficiently effective beyond simple updates due to the limitation of heuristic rules.

6.3 Comment Generation

Source code comment generation has been studied by many researchers previously. In earlier studies, scholars tend to use template-based approaches [6, 11, 12]. However, a well-designed template requires expert domain knowledge, which is not easy work. Consequently, IR-based approaches [35, 46] have been proposed. To generate comments for Java methods, Sridhara et al. [35] use summary information in source code and manually define templates. ColCom [46] proposed an approach that generates comments by reusing and tailoring comments of similar code snippets from open source projects. However, the retrieved comments may not correctly describe the semantics and behavior of code snippets, leading to the mismatches between code and comments. Recently, Neural Machine Translation (NMT) based models have been exploited to generate summaries for code snippets. CodeNN [19] is an early attempt that uses only code token sequences, followed by various approaches that utilize AST [2, 15, 16, 21, 22, 25], API knowledge [17], type information [4], global context [13, 25], reinforcement learning [42, 43], multitask and dual learning [44, 48, 50], and pretrained language models [8].

7 CONCLUSION

We propose a new approach, HatCUP, for just-in-time comment updating. To the best of our knowledge, this is the first work that considers the code structure change information. Combined with code change graph analysis and data flow dependency analysis, we introduce a syntax change encoder together with a structure-guided attention mechanism to more fully utilize code structure change hints. Additionally, the edit or non-edit mechanism, which is aimed at generating a sequence of edit actions to mimic human editing behavior, has proven better suited to the comment updating task than traditional approaches. Our results demonstrate that HatCUP outperforms the two state-of-the-art techniques and can substantially reduce developers’ efforts in updating comments.

ACKNOWLEDGMENTS

We thank the anonymous reviewers for their constructive comments. This research was supported, in part by NSFC 61832009, Cooperation Fund of Huawei-Nanjing University Next Generation Programming Innovation Lab (No. YBN2019105178SW27, No. YBN2019105178SW32). Any opinions, findings, and conclusions in this paper are those of the authors only and do not necessarily reflect the views of our sponsors.
REFERENCES

[1] Wasi Ahmad, Saikat Chakraborty, Baishakhi Ray, and Kai-Wei Chang. 2020. A Transformer-based Approach for Source Code Summarization. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: Association for Computational Linguistics, Online. 4998–5007. https://doi.org/10.18653/v1/2020.acl-main.449

[2] Uri Alon, Shaked Brody, Omer Levy, and Eran Yahav. 2018. code2seq: Generating sequences from structured representations of code. arXiv preprint arXiv:1806.01480 (2018).

[3] Satanjeev Banerjee and Alon Lave. 2005. METEOR: An automatic metric for MT evaluation with improved correlation with human judgments. In Proceedings of the acl workshop on intrinsic and extrinsic evaluation measures for machine translation and/or summarization. 65–72.

[4] RuiYi Cai, Zhihao Liang, Boyan Xu, Zijian Li, Yuexing Hao, and Yan Chen. 2020. TAG: Type Auxiliary Guiding for Code Comment Generation. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics. 291–301.

[5] Sergio Cozzetti B. de Souza, Nicolas Anguetel, and Käthia M. de Oliveira. 2005. A Study of the Documentation Essential to Software Maintenance. In Proceedings of the 23rd Annual International Conference on Design of Communication: Documenting & Designing for Perceptive Information (Coventry, United Kingdom) (SIGDOC ’05). Association for Computing Machinery, New York, NY, USA, 68–75. https://doi.org/10.1145/1085313.1085331

[6] Brian P. Eddy, Jeffrey A Robinson, Nicholas A Kraft, and Jeffrey C Carver. 2013. Evaluating source code summarization techniques: Replication and expansion. In 2013 21st International Conference on Program Comprehension (ICPC). IEEE, 13–22.

[7] Jean-Rémy Falleri, Floreai Morandat, Xavier Blanc, Mattias Martinez, and Martin Monrquez. 2014. Fine-Grained and Accurate Source Code Differencing. In Proceedings of the 29th ACM/IEEE International Conference on Automated Software Engineering (Vasteras, Sweden) (ASE ’14). Association for Computing Machinery, New York, NY, USA, 313–324. https://doi.org/10.1145/2642957.2642982

[8] Zhangyin Feng, Duyu Guo, Duyu Tang, Xin Duan, Xiaoqiang Feng, Min Gong, Linjun Shou, Bing Qin, Ting Liu, Daxin Jiang, et al. 2020. CodeBERT: A Pre-Trained Model for Programming and Natural Languages. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing; Finding Patterns. 1536–1547.

[9] Zhipeng Gao, Xin Xia, David Lo, John Grandy, and Thomas Zimmermann. 2021. Automating the removal of obsolete TODO comments. In Proceedings of the 29th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering. 218–229.

[10] Diederik P Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980 (2014).

[11] Alexander LeClair, Sahil Haque, Lingfei Wu, and Collin McMillan. 2020. Improved code summarization via a graph neural network. In Proceedings of the 28th International Conference on Program Comprehension. 184–195.

[12] Alexander LeClair, Siyuan Jiang, and Collin McMillan. 2019. A neural model for generating natural language summaries of program subroutines. In 2019 IEEE/ACM 41st International Conference on Software Engineering (ICSE). IEEE, 795–806.

[13] Srinivasan Iyer, Ioannis Konstas, Alvin Cheung, and Luke Zettlemoyer. 2016. Generating sequences from structured representations of code. arXiv preprint arXiv:1606.00001 (2016).

[14] Diederik P Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980 (2014).

[15] Sonia Haiduc, Jairo Aponte, and Andrian Marcus. 2010. Supporting program comments more useful?. In Proceedings of the 17th Working Conference on Reverse Engineering. IEEE, 35–44.

[16] Alexander LeClair, Sahil Haque, Lingfei Wu, and Collin McMillan. 2019. A neural model for generating natural language summaries of program subroutines. In 2019 IEEE/ACM 41st International Conference on Software Engineering (ICSE). IEEE, 795–806.

[17] Bohon Li, Shangwen Wang, Kai Liu, Xaoyoung Mao, and Tegawendé F Bissyandé. 2021. Automated Comment Update: How Far Are We? In 2021 IEEE/ACM 29th International Conference on Program Comprehension (ICPC). IEEE, 36–46. https://doi.org/10.1109/ICPC52881.2021.00013

[18] Sheena Panthapalackal, Milos Gligoric, Raymond J. Mooney, and Juny-Jessy Li. 2020. Associating Natural Language Comment and Source Code Entities. Proceedings of the AAAI Conference on Artificial Intelligence, 34, 05 (Apr. 2020), 8592–8599. https://doi.org/10.1609/aaai.v34i05.6382

[19] Michele Tufano, Jevgenija Pantiuchina, Cody Watson, Gabriele Bavota, and Oriol Vinyals. 2015. Pointer Networks. In Advances in Neural Information Processing Systems 28. 380–388.

[20] Oriol Vinyals, Meire Fortunato, and Navdeep Jaitly. 2015. Pointer Networks. In Advances in Neural Information Processing Systems 28. 380–388.

[21] Sheena Panthapalackal, Milos Gligoric, Raymond J. Mooney, and Juny-Jessy Li. 2020. Associating Natural Language Comment and Source Code Entities. Proceedings of the AAAI Conference on Artificial Intelligence, 34, 05 (Apr. 2020), 8592–8599. https://doi.org/10.1609/aaai.v34i05.6382

[22] Oriol Vinyals, Meire Fortunato, and Navdeep Jaitly. 2015. Pointer Networks. In Advances in Neural Information Processing Systems 28. 380–388.
[43] Wenhua Wang, Yuqun Zhang, Yulei Sui, Yao Wan, Zhou Zhao, Jian Wu, Philip Yu, and Guandong Xu. 2020. Reinforcement-learning-guided source code summarization via hierarchical attention. *IEEE Transactions on software Engineering* (2020).

[44] Bolin Wei, Ge Li, Xin Xia, Zhiyi Fu, and Zhi Jin. 2019. Code Generation as a Dual Task of Code Summarization. *Advances in Neural Information Processing Systems* 32 (2019), 6563–6573.

[45] Fengcai Wen, Csaba Nagy, Gabriele Bavota, and Michele Lanza. 2019. A Large-Scale Empirical Study on Code-Comment Inconsistencies. In 2019 IEEE/ACM 27th International Conference on Program Comprehension (ICPC). IEEE, 53–64. https://doi.org/10.1109/ICPC.2019.00019

[46] Edmund Wong, Taiyue Liu, and Lin Tan. 2015. Clocom: Mining existing source code for automatic comment generation. In 2015 IEEE 22nd International Conference on Software Analysis, Evolution, and Reengineering (SANER). IEEE, 380–389.

[47] Xin Xia, Lingfeng Bao, David Lo, Zhenchang Xing, Ahmed E Hassan, and Shaping Li. 2017. Measuring program comprehension: A large-scale field study with professionals. *IEEE Transactions on Software Engineering* 44, 10 (2017), 951–976.

[48] Rui Xie, Wei Ye, Jinan Sun, and Shikun Zhang. 2021. Exploiting Method Names to Improve Code Summarization: A Deliberation Multi-Task Learning Approach. In 2021 IEEE/ACM 29th International Conference on Program Comprehension (ICPC). IEEE.

[49] Wei Xu, Courtney Napoles, Ellie Pavlick, Quanze Chen, and Chris Callison-Burch. 2016. Optimizing statistical machine translation for text simplification. *Transactions of the Association for Computational Linguistics* 4 (2016), 401–415.

[50] Wei Ye, Rui Xie, Jingli Zhang, Tianxiang Hu, Xiaoyin Wang, and Shikun Zhang. 2020. Leveraging Code Generation to Improve Code Retrieval and Summarization via Dual Learning. Association for Computing Machinery, New York, NY, USA, 2389–2319. https://doi.org/10.1145/3366423.3380295

[51] Jian Zhang, Xu Wang, Hongyu Zhang, Hailong Sun, and Xudong Liu. 2020. Retrieval-based neural source code summarization. In 2020 IEEE/ACM 42nd International Conference on Software Engineering (ICSE). IEEE, 1385–1397.