ECMG: Exemplar-based Commit Message Generation

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ABSTRACT
Commit messages concisely describe the content of code diffs (i.e., code changes) and the intent behind them. Recently, many approaches have been proposed to generate commit messages automatically. The information retrieval-based methods reuse the commit messages of similar code diffs, while the neural-based methods learn the semantic connection between code diffs and commit messages. However, the reused commit messages might not accurately describe the content/intent of code diffs and neural-based methods tend to generate high-frequent and repetitive tokens in the corpus. In this paper, we combine the advantages of the two technical routes and propose a novel exemplar-based neural commit message generation model, which treats the similar commit message as an exemplar and leverages it to guide the neural network model to generate an accurate commit message. We perform extensive experiments and the results confirm the effectiveness of our model.

CCS CONCEPTS
• Computer systems organization → Embedded systems; Redundancy; Robotics; • Networks → Network reliability.

KEYWORDS
datasets, neural networks, gaze detection, text tagging

1 INTRODUCTION
Commit messages of code diffs are concise natural language descriptions that summarize what (content) the code changes are or why (intent) the code is changed. However, it is difficult to write high-quality commit messages due to the lack of time or clear motivation. Thus, it would be necessary and useful to generate commit messages automatically.

Over the years, many approaches have been proposed to generate commit messages automatically. Early studies [5, 21] are mainly based on predefined rules or templates, which may not cover all situations or infer the intention behind code changes. Later, some studies [8, 9, 15] adopt information retrieval (IR) techniques to reuse commit messages of similar code diffs. Recently, many neural-based methods [10, 13, 14, 17, 26] have been proposed to learn code diff representation and translate it into the commit message.

Although the above methods show promising performance, there are certain limitations. (1) For IR-based methods, the reused commit messages might not correctly describe the content/intent of code diffs since simple reuse does not consider the different information of the current code diff. (2) Neural-based methods tend to generate high-frequency and repetitive tokens in the corpus, and the generated commit messages have the problem of insufficient information and poor readability.

We use four real cases shown in Table 1 to further illustrate the above limitations. References are human-written commit messages. For IR-based method NNGen, the reused commit messages are inaccurate. For example, the unknown identifier (“netty”) is in Example 1, the class name in Example 2 is wrong (“ServiceManage” instead of “service”), the intent does not match (“description” instead of “source url”) in Example 3, and a completely irrelevant commit message in Example 4. For neural-based methods NMT, the generated commit messages suffer from insufficient information (Example 2, 3) and poor readability (Example 1, 4) problems. Thus, both of them cannot generate accurate commit messages.

To overcome the above mentioned limitations, we propose a novel model ECMG (Exemplar-based Commit Message Generation), which retrieves a similar commit message as an exemplar, guides the neural model to learn the content of the code diff and the intent behind the code diff, and generates the readable and informative commit message. The key idea of our approach is retrieval and refining. Specifically, we first retrieve the similar code diff paired with the commit message through an IR-based method. Then, instead of directly reusing the similar commit message as
Table 1: Motivating examples. References are the human-written commit messages. Tokens appeared in the reference are marked in blue for easy understanding.

| Example 1: Code diff |
|----------------------|
| `spring-projects:spring-framework/build.gradle.py` |
| `54 54 ext.openjpaVersion = "2.2.2"` |
| `55 ext.protobufVersion = "2.0.1.RELEASE"` |
| `56  - ext.reactorVersion = "2.0.1.RELEASE"` |
| `56 + ext.reactorVersion = "2.0.2.RELEASE"` |
| `57 57 ext.slf4jVersion = "1.7.12"` |

Reference: upgrade to reactor 2.0.2

NMT: upgrade to reactor 2.0.2

ECMG: upgrade to reactor 2.0.2

Example 2:

Reference: add duration-based overloads to service

NMT: add problem description for LargestPrimeDivisor

ECMG: add duration-based overloads to service

Example 3:

Reference: update to maven shade plugin 3.2.4

NMT: merge pull request #22227 from anshlykov

ECMG: upgrade to maven shade plugin 3.2.4

Example 4:

Reference: add problem source url for LargestPrimeDivisor

NMT: upgrade to maven plugin 3.2.4

ECMG: upgrade to reactor 2.0.2

3 PROPOSED APPROACH

An overview of our approach ECMG is shown in Figure 1. We first use a simple retrieval model to obtain the similar code diff and the commit message from a large parallel corpus and then adopts a neural model to refine the commit message according to the input and the similar code diff.

3.1 Retrieval Module

Inspired by previous work [8, 15], we choose the lexical-level similarity as retrieval metric, which can efficiently measure the similarity of code diffs without training. Specifically, given a code diff and training corpus, we obtain the TF-IDF based code diff vector by calculating the term frequency of each token of the code diff and multiplying it by the inverse document (train corpus) frequency of this token. Then we retrieve the most similar code diff based on the cosine similarity between two code diff vectors. We use a widely-used search engine Lucene to efficiently retrieve the most similar code diff from the training corpus based on the lexical-level similarity.
3.2 Refining Module

We treat the retrieved commit message as an exemplar and use it to guide the neural model to generate an accurate commit message. As shown in Figure 1, our refining module consists of four components: three encoders, a similarity calculation module, an attention module, and a decoder. First, three LSTM-based encoders are adopted to obtain the hidden states of the input code diff \((x_1^d, x_2^d, ..., x_t^d)\), the similar code diff \((x_1^s, x_2^s, ..., x_m^s)\), and similar commit message \((c_1, c_2, ..., c_m)\) (step 1 in Figure 1), where subscripts \(i, m, n\) are the length of the input code diff, the similar code diff, and the similar commit message, respectively.

Second, the semantic similarity \((ss)\) between the input code diff and the similar code diff is computed by feeding their representation \(x_i^d\) and \(x_m^s\) to the similarity calculation module (step 2):

\[
ss = \sigma(W_s[x_i^d, x_m^s])
\]

where \(\sigma\) is the sigmoid activation function and \(W_s\) is a learnable matrix.

Third, since attention mechanism \([1]\) can pay attention to the relevant parts of the code diff during the decoding process, we adopt the attention module to combine the information from the input code diff and similar commit message guided by semantic similarity \((ss)\) when generating the next commit message token \(y_i\). Specifically, the two context vectors \(c_i^d\) and \(c_i^s\) are computed as a weighted sum of the hidden states of the input code diff and similar commit message, respectively (step 3):

\[
c_i^d = \sum_{j=1}^{t} a_j x_j^d, \quad a_{ij} = \frac{\exp(e_{ij})}{\sum_{j=1}^{t} \exp(e_{ij})}
\]

where \(e_{ij} = a(h_{i-1}, x_j^d)\) is an alignment module which measures how well the \(j\)-th inputs and the \((i-1)\)-th output relate. \(h_{i-1}\) is the hidden state of the previous token during generating the commit message word by word. Following Bahdanau et al. \([1]\), we use a MLP (Multi-layer Perceptron) as the alignment module. \(c_i^d\) is calculated in the same way as \(c_i^s\). Then, the extended context vector \(c_i^e\) is computed (step 3) by:

\[
c_i^e = W_m c_i^d + (1 - ss) + \text{em} \times ss
\]

where \(W_m\) is a learnable projection matrix to map \(c_i^d\) to the space \(\text{em}\).

Finally, ECMG starts the decoding process with an initial \(<\text{START}>\) token to generate the commit message sequence word by word (step 4):

\[
p(y_i|y_1...y_{i-1}, x^d, x^s, \text{em}) = p(y_i|y_{i-1}, y_1, c_{i-1})
\]

where \(y_1, ..., t\) is the one-hot vector of commit message token. We use Cross-Entropy as the loss function and apply AdamW for optimization.

4 EXPERIMENTS

4.1 Experimental Setup

Dataset and Pre-processing. In our experiment, we adopt a large dataset MCDM \([23]\) with five programming languages (PL): Java, C\#, C++, Python and JavaScript (JS for short). For each PL, MCDM collects \(\text{commits}\) from the top 100 starred repositories on Github and then filters the redundant messages (such as rollback commits) and noisy messages defined in Liu et al. \([15]\). Finally, to balance the size of data, they randomly sample and retain 45,000 \(\text{commits}\) for each PL. Each \(\text{commit}\) contains a code diff, a commit message, the name of the repository, and the timestamp of \(\text{commit}\), etc. The partitioning of train/validation/test sets follows the original dataset and the partition ratios are 8:1:1. Following previous studies \([22]\), we split code tokens by camel case and snake case for pre-processing.

Evaluation Metrics. We evaluate the quality of the generated messages using four metrics: BLEU \([18]\), Meteor \([2]\), Rouge-L \([12]\) and Cider \([25]\). There are many variants of BLEU being used to measure the generated message. We choose B-Norm (the BLEU-4 results in this paper are B-Norm), which correlates with human perception the most \([23]\).

Baselines. We compare ECMG with four neural-based methods CommitGen \([10]\), CoDiSum \([26]\), NMT \([17]\), and PtrGNCMsg \([13]\), as well as two IR-based methods NNGen \([15]\) and Lucene. All except Lucene are introduced in Section 2. Lucene is a traditional IR baseline, which uses TF-IDF to represent a code diff as a vector and searches the similar code diff based on the cosine similarity between two vectors.

Hyperparameters. The embedding size and hidden state size of LSTM are 256. The batch size is 128. The learning rate is \(10^{-3}\). The hyperparameters are tuned empirically. More details about hyperparameters and the experimental settings are in the Appendix.

4.2 How does ECMG perform compared with baseline approaches?

| Model     | Java  | C#   | C++  | Python | JS   | Avg.  |
|-----------|-------|------|------|--------|------|-------|
| CommitGen | 12.39 | 18.14| 11.58| 11.10  | 17.40| 14.12 |
| CoDiSum   | 14.00 | 12.73| 12.46| 14.63  | 11.24| 13.01 |
| NMT       | 13.39 | 17.32| 11.56| 11.53  | 17.08| 14.18 |
| PtrGNCMsg | 15.33 | 19.72| 13.07| 15.99  | 19.58| 16.74 |
| NNGen     | 17.81 | 22.92| 13.69| 16.64  | 18.03| 17.82 |
| Lucene    | 15.53 | 22.75| 13.66| 16.04  | 17.51| 17.10 |
| ECMG      | 18.49 | 24.73| 15.31| 17.35  | 20.92| 19.36 |

Table 2: Comparison with baselines under BLEU-4.

We evaluate the effectiveness of ECMG by comparing it with the baselines on the MCDM dataset. Table 2 shows the BLEU-4 scores\(^2\). We can see that IR-based models NNGen and Lucene outperform other baselines on average (Avg.). However, the retrieved commit messages may not be consistent with the input code diff (four real examples are shown in Table 1). Our approach jointly models the retrieved commit messages and input code diffs (Equation 3), and generates the final commit messages. Thus, our model performs the best among all approaches on 5 programming languages. Specifically, ECMG improves the performance of Lucene and NMT by 11.14% and 36.53 % on average, respectively. The results demonstrate that our model can take advantage of both retrieval and neural machine translation techniques.

\(^2\)Our conclusion also holds under the other three metrics. Please see the Appendix for detailed experimental results.
4.3 What is the generalization ability of ECMG?
To further study the generalization of our model, we evaluate ECMG when the dataset is split by projects. Following previous work [11, 23], we partition each PL’s dataset into training/validation/test by projects in proportion with 8:1:1, so that samples from the same project can only exist in one partition. Then, we evaluate ECMG and baselines on this dataset.

| Model      | Java | C# | C++ | Python | JS | Avg. |
|------------|------|----|-----|--------|----|------|
| CommitGen  | 5.20 | 4.82 | 4.47 | 7.61   | 7.05 | 5.83 |
| CoDiSum    | 10.23 | 8.43 | 2.87 | 9.23   | 8.02 | 7.76 |
| NMT        | 7.94 | 5.95 | 5.73 | 5.29   | 7.39 | 6.46 |
| PtrGNCMsg  | 7.92 | 8.08 | 6.28 | 8.79   | 11.98| 8.61 |
| NNGen      | 5.67 | 9.89 | 3.90 | 4.66   | 5.72 | 5.97 |
| Lucene     | 5.29 | 10.28 | 3.82 | 4.68   | 5.43 | 5.90 |
| ECMG       | 8.38 | 11.03 | 6.78 | 11.03  | 9.39 | 9.32 |

Table 3: BLEU-4 results of the split by project setting.

Table 3 shows the performance of models on the dataset split by projects. We can see that neural-based approaches perform better than IR-based approaches on average, which means that the neural-based models are able to better generalize on new projects compared to the IR-based models. Our model combining retrieval and neural techniques can perform well on the dataset split by projects in almost all PLs. The result on the JS dataset is an exception, where PtrGNCMsg performs better than ECMG. After preliminary analysis, we find that there are a large number of OOV words in the JS dataset, which can be addressed well by PtrGNCMsg’s pointer network. In future work, we will further investigate this issue.

| Model      | Java | C# | C++ | Python | JS | Avg. |
|------------|------|----|-----|--------|----|------|
| CommitGen  | 8.08 | 4.53 | 7.08 | 5.50   | 8.91 | 6.82 |
| CoDiSum    | 12.71 | 4.85 | 12.24 | 12.46  | 11.17 | 11.17|
| NMT        | 9.50 | 5.15 | 8.53 | 7.31   | 11.58| 8.41 |
| PtrGNCMsg  | 13.30 | 9.38 | 10.94 | 13.21  | 18.07| 12.98|
| NNGen      | 10.73 | 7.83 | 9.30 | 9.36   | 12.07| 9.86 |
| Lucene     | 10.92 | 7.24 | 9.34 | 9.90   | 11.51| 9.78 |
| ECMG       | 14.20 | 11.04 | 12.76 | 13.29  | 15.82| 13.42|

Table 4: BLEU-4 results of the split by timestamp.

5 CONCLUSION
This paper proposes a new exemplar-based commit message generation model. It combines the retrieval technique and neural model and generates informative commit messages. Experimental results on a large multi-programming-language dataset have demonstrated the effectiveness of ECMG over the recent approaches. Our replication package and the appendix are available at https://anonymous.4open.science/r/ECMG.

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