Evaluating Commit Message Generation: To BLEU Or Not To BLEU?

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ABSTRACT
Commit messages play an important role in several software engineering tasks such as program comprehension and understanding program evolution. However, programmers neglect to write good commit messages. Hence, several Commit Message Generation (CMG) tools have been proposed. We observe that the recent state of the art CMG tools use simple and easy to compute automated evaluation metrics such as BLEU4 or its variants. The advances in the field of Machine Translation (MT) indicate several weaknesses of BLEU4 and its variants. They also propose several other metrics for evaluating Natural Language Generation (NLG) tools. In this work, we discuss the suitability of various MT metrics for the CMG task. Based on the insights from our experiments, we propose a new variant specifically for evaluating the CMG task. We re-evaluate the state of the art CMG tools on our new metric. We believe that our work fixes an important gap that exists in the understanding of evaluation metrics for CMG research.

CCS CONCEPTS
- Software and its engineering → Software verification and validation.

KEYWORDS
BLEU, METEOR, Commit Message Generation

1 INTRODUCTION
Commit messages are Natural Language (NL) descriptions of code changes. Developers submit such textual description along with their code changes. These messages, called as commit messages or log messages, are important to the total software development process and reduce the time taken to understand the code change. Often, developers provide low quality commit messages or even no message. Dyer et al. [16] analyzed 23,000 Java projects on SourceForge1 and reported that around 14% of commit messages were empty. Therefore, CMG tools are required. Commit Message Generation (CMG) tools take code changes as input and produce commit messages as output.

Automatically generated commit messages are evaluated against the ground-truth. Human evaluation would provide the best assessments, but it is expensive and time-consuming. Automated evaluation of the CMG task so far has been limited to reusing metrics popularly used for various Machine Translation (MT) and Natural Language Generation (NLG) tasks.

The first known automatic evaluation metric BLEU [15] relied on n-gram precision. BLEU computes word overlap between the predicted and the reference gold-standard written by the project members. METEOR [2] is another metric which is based on unigram matches on the words and also their stems with additional synonyms database. In addition to these, numerous other metrics [18] have evolved for automatically evaluating Machine Translation (MT) systems. In addition to semantic scoring through word overlap, these metrics propose different ways to penalize the length, and score word order alignment.

BLEU and its variants may not be suitable for assessing commit messages. Reiter [17] claims that the assumption of word overlap correlating with real-world utility needs to be validated through user studies or task performance. It is unclear, which metric is most appropriate for evaluating the CMG task.

The fundamental factors behind the widely used MT based metrics are semantic scoring, length penalty and word order alignment. In addition, Tao et al. [20] observe that case sensitivity and smoothing could be potential factors affecting CMG evaluation. The relevance of these factors with respect to commit messages have not been studied. Understanding their effect on commit message quality as per expert perception i.e., as per human evaluation will help us in deciding the metric to use for evaluating the commit messages. Hence, we ask the following research questions.

RQ1 What factors affect commit message quality as per expert perception?
RQ2 Which metric is best suited to evaluate commit messages?
RQ3 How do the CMG tools perform on the new metric?

To the best of our knowledge, this is the first work to evaluate the influence of various factors on existing metrics, and also propose a metric specifically to evaluate CMG tools.

1https://sourceforge.net/
2 BACKGROUND

2.1 Commit Message Generation Tools
Several CMG tools have been proposed. Jiang et al. [8] proposed CommitGen which uses an attentional Recurrent Neural Network (RNN) encoder-decoder based Neural Machine Translation (NMT) model Nematus to translate code change diffs into commit messages. The CommitGen model is trained using a corpus of code changes and human-written commit messages from the top 1k Github projects. NMT proposed by Loyola [12] in 2017, is similar to CommitGen, but it is guided by a global attention model proposed by Luong et al. [13] instead of the Bahdanau attention model in NMT. This model is trained using code changes and human-written commit messages from popular Github projects across multiple programming languages. NNGen proposed by Liu et al. [11] in 2018, is a retrieval-based model which is based on the Nearest Neighbour and Bag-of-Words (BOW) approach. The NNGen model is trained on a filtered version of the CommitGen dataset.

2.2 Automated Evaluation in Machine Translation
Several automated metrics have been proposed [4]. The prominent MT evaluation metrics used in evaluating CMG tools can be broadly categorised as a) Precision based, b) Recall based, c) F-Score based, and d) Edit Distance based metrics.

Precision based Metrics. During word matches, precision based metrics score higher if there are more matches for words in the predicted text. BLEU4 [16] is a classic example of a precision based metric. BLEU4 is calculated as shown in Equation 1 where BP is the brevity penalty, $w_k$ refers to the empirically chosen weight of each k-gram and $p_k$ is the match score for the k-gram.

$$\text{BLEU4} = \text{BP} \cdot \exp \left( \sum_{k=1}^{n} w_k \cdot \log(p_k) \right)$$

There are several variants of BLEU such as BLEUMoses [9], BLEUNorm [12] and BLEUCC [5]. BLEUNorm applies smoothing to the match score as shown in Equation 2, where $\text{Count}_{\text{match}}$ is the number of n-gram matches between predicted and reference (Ref) text while $\text{Count}(n\text{-gram})$ refers to the number of n-grams.

$$\text{ROUGE-n} = \frac{\sum_{n\text{-grams} \in \text{Ref}} \text{Count}_{\text{match}}(n\text{-gram})}{\sum_{n\text{-grams} \in \text{Ref}} \text{Count}(n\text{-gram})}$$

Recall based Metrics. During word matches, recall based metrics score higher if more words are recalled considering each word in the reference text. ROUGE [10] is an example of a recall based metric, which is calculated as shown in Equation 2, where $\text{Count}_{\text{match}}$ is the number of n-gram matches between predicted and reference (Ref) text while $\text{Count}(n\text{-gram})$ refers to the number of n-grams.

$$\text{ROUGE-n} = \frac{\sum_{n\text{-grams} \in \text{Ref}} \text{Count}_{\text{match}}(n\text{-gram})}{\sum_{n\text{-grams} \in \text{Ref}} \text{Count}(n\text{-gram})}$$

F-Score based Metrics. METEOR is an F-Score based metric. It considers a fragmentation penalty, calculated as Frag Penalty = 0.5 + $\frac{\# \text{chunks}}{\# \text{unigrams matched}}$ where chunks are contiguous predicted unigrams mapped to contiguous unigrams in the reference. The final METEOR score is thus calculated using Equation 3.

$$\text{METEOR} = \text{F-score} \ast (1 - \text{Frag Penalty})$$

Edit Distance based Metrics. In Edit Distance based metrics, number of word operations such as insertions, deletions and substitutions are used to compute the edit distance between the given and reference texts. TER [19] is an example. The TER metric score is calculated as shown in Equation 4.

$$\text{TER} = \frac{\# \text{substitutions} + \# \text{deletions} + \# \text{insertions}}{\# \text{words in reference text}}$$

3 EXPERIMENTAL SETUP

3.1 Selection of Factors
Commit messages although defined as NL descriptions of code changes, are different from normal NL text. To address RQ1, we gather several factors from the various evaluation metrics and related literature.

Papineni et al. [16] propose that a good evaluation metric should ensure that the predicted text be neither too long nor too short. Hence precision based metrics such as BLEU [16] and its variants use length penalizers to penalize shorter predictions. "The gunman killed the cop" and "The cop killed the gunman" are not the same sentences. In order to handle ordering, a simple bag of words representation is not suitable. Metrics such as METEOR [2] and METEOR-NEXT [6] account for the alignment of matched words in the predicted and reference sentences. The pair "Update change" and "Updated changes" essentially convey the same meaning, although exact-word matchers in BLEU and ROUGE would give a score of zero instead of one. Hence, in addition to exact matches, stemmed and paraphrased matchings are also considered by METEOR and METEOR-NEXT. Banerjee and Lavie [2] convert text to lowercase as a part of preprocessing in the implementation of METEOR. Punctuations are often treated as separate words by the default parsers and matchers in various programming languages which heavily affects the scores. BLEU4 geometrically averages the n-gram matches, thereby, giving zero score for pairs like "added chain of responsibility class diagram" and "added chain diagram" due to missing n-gram matches of order three or above. BLEUCC and BLEUNorm are smoothed versions of BLEU. Therefore, we consider the factors namely length, word order, semantics, case, punctuation and smoothing as shown in Table 2.

3.2 Comparison with Human Annotations
We use a dataset of 100 human evaluated reference and predicted commit message pairs shared by Tao et al. [20]. The data is manually labelled between 0 to 4 by three domain experts and validated for reliability. We took the arithmetic mean to obtain a single averaged score of human evaluation for each pair of reference and predicted commit messages. In our experiments, we compare the scores produced using the MT metrics discussed in Section 2.2 with these human annotation scores using Spearman’s correlation [21]. We do it once in the presence of the factor and once in its absence. Table 2 lists the modifications in the metric formulae due to inclusion and exclusion of the various factors used in our study.

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Table 1: Spearman’s correlations of metrics with human judgments w.r.t. potential factors. “Clean” refers to the correlation of metric in its original formulation without any changes.

| Metric       | Length | Word Order | Semantics | Case Folding | Punctuation | Smoothing | Clean |
|--------------|--------|------------|-----------|--------------|-------------|-----------|-------|
|              | Without | With      | Without | With      | Without | With      | Without | With      | Without | With      | Without | With      | Without | With      |
| BLEU4        | 0.69    | 0.705      | 0.705    | 0.705      | 0.705    | 0.717     | 0.705   | 0.717     | 0.705   | 0.705     | 0.705   | 0.691  | 0.681  | 0.705   |
| BLEUNorm     | 0.683   | 0.691      | 0.691    | 0.691      | 0.691    | 0.703     | 0.691   | 0.699     | 0.691   | 0.691     | 0.691   | 0.691  | 0.691  | 0.691   |
| BLEUCC       | 0.683   | 0.681      | 0.681    | 0.681      | 0.681    | 0.691     | 0.681   | 0.693     | 0.681   | 0.681     | 0.681   | 0.681  | 0.681  | 0.681   |
| METEOR       | 0.748   | 0.748      | 0.725    | 0.748      | 0.707    | 0.748     | 0.748   | 0.807     | 0.748   | 0.748     | 0.748   | 0.748  | 0.748  | 0.748   |
| METEOR-NEXT  | 0.761   | 0.761      | 0.756    | 0.761      | 0.722    | 0.761     | 0.761   | 0.822     | 0.761   | 0.761     | 0.761   | 0.761  | 0.761  | 0.761   |
| ROUGE1       | 0.723   | 0.723      | 0.723    | 0.723      | 0.723    | 0.723     | 0.723   | 0.723     | 0.723   | 0.723     | 0.723   | 0.723  | 0.723  | 0.723   |
| ROUGE2       | 0.443   | 0.443      | 0.443    | 0.443      | 0.443    | 0.443     | 0.443   | 0.443     | 0.443   | 0.443     | 0.443   | 0.443  | 0.443  | 0.443   |
| ROUGEL       | 0.728   | 0.728      | 0.728    | 0.728      | 0.728    | 0.728     | 0.728   | 0.728     | 0.728   | 0.728     | 0.728   | 0.728  | 0.728  | 0.728   |
| TER          | 0.568   | 0.568      | 0.568    | 0.568      | 0.568    | 0.568     | 0.568   | 0.568     | 0.568   | 0.568     | 0.568   | 0.568  | 0.568  | 0.568   |

Table 2: Computation after addition/removal of factors in metrics. Here, B4 is BLEU4, BN is BLEUNorm, BCC is BLEUCC, M is METEOR and MN is METEORNEXT, FP is Fragmentation Penalty.

| Factor        | Metrics | Formula |
|---------------|---------|---------|
| Length        | B4, BN, BCC | \(exp \left( \frac{1}{k} \sum_{k=1}^{n} w_k \log(p_k) \right) \) |
| Word Order    | M, MN   | F-score\(\text{exact matches} \) \* F-score\(\text{(1 – FP)} \) |
| Semantics     | M, MN   | F-score\(\text{exact matches} \) \* F-score\(\text{(1 – FP)} \) |
| Case          | All     | No case folding. |
| Punctuation   | All     | No Change. Remove lower case text. |
| Smoothing     | B4, BN, BCC | No Change. |

Table 3: Performances of CMG models.

| Model        | C++ | C# | Java | Js | Py | Avg |
|--------------|-----|----|------|----|----|-----|
| CommitGen    | 11.94 | 18.35 | 9.63 | 18.11 | 8.27 | 13.26 |
| NMT          | 11.69 | 17.96 | 10.7 | 15.38 | 9.34 | 12.65 |
| NNGen        | 13.82 | 16.89 | 7.4 | 18.25 | 14.27 | 14.13 |

3.3 CMG Tools, Metrics and the Commit Dataset

To answer RQ3, we consider the CMG tools discussed in Section 2.1. Different CMG tools use different datasets for their evaluation. In order to compare them, we need a unified dataset. NMT and NNGen use datasets consisting of only Java code changes that are relatively small (i.e., not exceeding 50K). We follow Tao et al. [20] and use their Multi-Language Commit Message (MCMD) dataset. This dataset has 3.6M commit messages in five popular Programming Languages (PLs) from the top 100 starred projects on GitHub.

4 RESULTS

4.1 RQ1: What factors affect commit message generation as per expert perception?

Table 1 shows the Spearman’s correlation values with and without the six factors applied to the various metrics. A factor is assumed to affect the evaluation of CMG if its presence in a metric increases the Spearman’s correlation with human evaluation. The observations from the Table 1 indicate that the factors Length, Word Alignment, Semantic Scoring, Lower-Casing and Punctuation Removal, when incorporated in the corresponding metrics, improve correlation with human judgements. While inclusion of the factor Smoothing reduces the correlation with human evaluation.

4.2 RQ2: Which metric is best suited to evaluate commit messages?

None of the standard MT metrics discussed in Section 2.2 have all the affecting factors incorporated in them. This motivates the construction of a new metric. We propose a modified version of the METEOR-NEXT metric, called Log-MNEXT. Section 5 discusses the construction of Log-MNEXT. To validate the goodness of Log-MNEXT to the existing MT metrics, its Spearman’s correlation with human evaluation score is calculated and compared with that of the other metrics in Table 1.

4.3 RQ3: How do the CMG tools perform on the new metric?

The CMG models discussed in Section 2.1 are evaluated using variants of BLEU. In a similar experimental setup as that of Tao et
al. [20], we compare the performances of CommitGen, NMT and NNGen using Log-MNEXT metric. The MCMD dataset is split across various programming languages (PLs). The average Log-MNEXT scores in percentages, across datasets of different PLs for each of the models, is given in Table 3. Overall, the retrieval-based model NNGen outperforms CommitGen and NMT, with an average Log-MNEXT score of 14.13.

NNGen performs the best when evaluated on the MCMD dataset using the Log-MNEXT metric.

5 LOG-MNEXT METRIC

METEOR-NEXT incorporates most of the relevant factors. Hence, we base Log-MNEXT on METEOR-NEXT. In addition to exact word matchings, Log-MNEXT also performs stemmed and paraphrased matchings as in METEOR and METEOR-NEXT metrics. Log-MNEXT performs string lower-casing and removes punctuation as a preprocessing step, before looking for word matches or performing word alignment between the predicted and reference texts.

Consider the case where we have identical reference and predicted messages. Any human annotator will not penalize this. However, the denominator of the fragmentation penalty factor Frag Penalty of METEOR-NEXT given by Equation 5 depends on the number of unigram matches. Hence, it penalizes this case. Log-MNEXT improves on the Frag Penalty by assigning no penalty score in such cases.

$$\text{Frag Penalty} = \begin{cases} 0 & \text{if Ref} \equiv \text{Pred} \\ \beta \times \left[ \frac{\text{# unigrams matched}}{\text{# chunks}} \right] & \text{otherwise} \end{cases} \tag{5}$$

The Log-MNEXT score is finally obtained using equation 6.

$$\text{Log-MNEXT} = \text{F-score } \cdot (1-\text{Frag Penalty}) \tag{6}$$

To get the F-Score, Precision (P) and recall (R) are calculated by assigning weights to the various unigram matchings.

$$P = \sum \frac{w_i m_i}{L_p} \quad \text{and} \quad R = \sum \frac{w_i m_i}{L_r} \tag{7}$$

where for a matcher type $i \in \{\text{exact match, stemmed match, synonym match}\}$, $w_i$ is the weight and $m_i$ is the number of matched unigrams. $L_p$ is the length of predicted text and $L_r$ is the length of reference text. The weighted F-score with $0 < \alpha < 1$ is calculated as $\frac{P R}{\alpha P + (1-\alpha)R}$.

6 RELATED WORK

There are works comparing [3, 7, 14, 18] automated evaluation metrics for machine translation. Our work is different from them because we discuss the suitability of metrics used in evaluating commit message generation tools. Tao et al.’s [20] work is the closest to our work. However, they limit their study to BLEU variants. They report that the models rank inconsistently across the different metrics. They find that BLEUNorm is most correlated to human annotations. They suggest smoothing and case sensitivity as two potential reasons for it to perform well. Finally, they report existence of heavy sensitivity of these metrics on the dataset. These are related and relevant to our work. However, we consider other popular metrics from MT and NLG for evaluation. We find that a new metric is necessary. Further, we propose the new metric and evaluate the performance of the existing models on the new metric.

7 FUTURE WORK

The results of our experiments emphasize on the use of the novel metric Log-MNEXT for evaluating commit messages. We now enlist key future directions.

Building larger human annotated dataset. For the purpose of this work, we have used existing human annotated dataset. The size of the dataset (100) leads to internal validity. We plan to build our own larger dataset, containing more number of reference and predicted commit message pairs. Claims made on the basis of such a dataset are expected to be more sound and strong.

Working on learning based metrics. This work limits to non-learning based i.e., simple and fast metrics such as BLEU. This may lead to external validity. This is mitigated to a large extent since the existing CMG tools use the fast metrics for evaluation for various reasons including the fact that even the learning based metrics have not been established to correlate significantly with human annotations better than the fast metrics. We plan to study learning based metrics in detail as future work.

Revising the Log-MNEXT metric. This work presents the most basic form of the metric Log-MNEXT. A major portion in the construction of the metric has been adapted from the existing METEOR-NEXT metric. Improvisations in the form of better synonym and paraphrase matching, cautious removal of punctuation from sentence pairs and careful case-folding before evaluation, are some important scopes of future work.

Building an exhaustive commit dataset. To compare the performances of the CMG tools on the Log-MNEXT metric, the MCMD dataset has been used. Although the language diversity in MCMD has been expanded to 5 popular PLs, it is still not exhaustive. Building an exhaustive dataset by including more PLs, is a direction of future work. However, appropriate caution is needed when generalizing our findings across PLs.

8 CONCLUSION

In spite of various drawbacks, BLEU continues to be the most popular metric to be used in the evaluation of CMG models. We identify various potential factors affecting CMG evaluation. The results of our experiments show the low correlation of BLEU with human evaluated scores. With an aim of using an evaluation metric which incorporates all valid factors, a new and novel metric Log-MNEXT is proposed. This metric has the highest correlation with human evaluations. Finally, we use this metric to compare the existing CMG models on the MCMD dataset and show that the NNGen model performs the best overall. We suggest that Log-MNEXT should be considered as the evaluation metric for CMG evaluation in future research, instead of BLEU or its variants.

We have shared the implementation [1] of Log-MNEXT for future research.
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