CommitBART: A Large Pre-trained Model for GitHub Commits

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Abstract

GitHub commits, which record the code changes with natural language messages for description, play a critical role for software developers to comprehend the software evolution. To promote the development of the open-source software community, we collect a commit benchmark including over 7.99 million commits across 7 programming languages. Based on this benchmark, we present CommitBART, a large pre-trained encoder-decoder Transformer model for GitHub commits. The model is pre-trained by three categories (i.e., denoising objectives, cross-modal generation and contrastive learning) for six pre-training tasks to learn commit fragment representations. Furthermore, we unify a “commit intelligence” framework with one understanding task and three generation tasks for commits. The comprehensive experiments on these tasks demonstrate that CommitBART significantly outperforms previous pre-trained works for code. Further analysis also reveals each pre-training task enhances the model performance.

1 Introduction

Large pre-trained models such as BERT (Devlin et al., 2019), GPT (Radford et al., 2019) and T5 (Raffel et al., 2020) have significantly improved state-of-the-art across a variety of natural language processing (NLP) tasks. These models are pre-trained on a large scale of unlabeled data with self-supervised objectives to learn contextual representations and then fine-tuned to multiple downstream tasks. Inspired by the great success of these models in NLP, recently a number of pre-trained models (Feng et al., 2020; Ahmad et al., 2021; Wang et al., 2021c) for programming languages (PL) have emerged in software engineering to advance the development of code intelligence. However, these works in the program scenario aim at learning the general program representation for a single function. The booming development of the open-source software industry has led to an unprecedented amount of projects hosted on Github*, which produces an extremely massive amount of commits. GitHub commits, which record the changed code (i.e., code changes) with the commit messages in natural language to describe the changed code, play a critical role for software developers to comprehend the evolution of software features at different stages of software development. To promote the development of the open-source software community, a specialized pre-trained model for “commit intelligence” is vital and meaningful for software developers.

The previous work CommitBERT (Jung, 2021) proposed to directly employ CodeBERT (Feng et al., 2020) to fine-tune a model for commit message generation (Jiang et al., 2017; Liu et al., 2020) (a task to automatically generate the natural language description given the input of the code changes) on the collected commit dataset (345K in total). However, CommitBERT did not pre-train a commit-specific pre-trained model on the commit data and this limits the performance on commit-related downstream tasks. Furthermore, the amount of the released data is far from satisfactory to the requirements for pre-training. In this work, we present CommitBART, a pre-trained encoder-decoder model based on BART (Lewis et al., 2019) architecture for commits to support both commit-related understanding tasks and generation tasks. Compared with current pre-trained models for code, we are the first to provide a large pre-trained model for commits and unify a “commit intelligence” framework to support multiple commit-related tasks.

Due to the lack of a large-scale commit benchmark, we collect a commit benchmark across 7 programming languages (i.e., C, CSharp, Java, Python, R, Scala, and SQL).
JavaScript, PHP, Python and Typescript). Specifically, we extract commits from the top 500 projects based on the star ranking for each programming language to construct this benchmark. We obtain over 7.99 million commit data in total and make it public to benefit the follow-up researchers. We pre-train CommitBART using six pre-training tasks that can be divided into three categories. Specifically, they can be classified into denoising objectives (text infilling and graph-guided token masking), cross-modal generation (PL2NL generation and PLNL2PL generation) and contrastive learning (NLPL alignment and SimCSE (Gao et al., 2021)). Besides text infilling (Lewis et al., 2019), to enhance semantic mapping between commit message and changed code, we design the objective of graph-guided token masking. It is designed to encourage the model to predict these tokens that both appear in the commit message and changed code. Furthermore, we design two cross-modal generation tasks: PL2NL generation task, which takes the changed code as input to generate its commit message, and PLNL2PL generation task, which takes the previous code as well as the commit message as the input to generate the updated code snippet. Both cross-modal generation tasks ensure that the model can generate high-quality code or natural language text about commits. We also design two contrastive learning-based objectives to enhance the semantics of code embeddings and message embeddings. The first NLPL alignment encourages the embedding of the changed code produced by the encoder to be closer to its corresponding message embedding and the second SimCSE takes the same input sequence to encoder twice with different dropout masks to aggregate semantic equivalent inputs.

We evaluate CommitBART with two widely concerned tasks for commits: security patch identification (understanding task) and commit message generation (generation task). We further propose two new commit-related generation tasks (i.e., positive code statements generation and updated code snippet generation). The extensive experiments illustrate that CommitBART achieves state-of-the-art performance on these tasks. Further analysis also reveals that each pre-training task enhances CommitBART to obtain better performance. The main contributions are summarized as follows:

- We collect a large-scale commit benchmark (over 7.99 million commits) across 7 programming languages and make it public for follow-up researchers.
- We are the first to present a large pre-trained model namely CommitBART for GitHub commits and it is pre-trained by the designed three categories for six pre-training tasks.
- We unify a “commit intelligence” framework with one understanding task and three generation tasks for commits. The extensive experimental results on these tasks have demonstrated that CommitBART achieves state-of-the-art performance against the baselines. We encourage the follow-up researchers to contribute more commit-related tasks to this framework.

2 Background

2.1 GitHub Commits

A commit usually consists of the changed code with its commit message to describe the purpose of the current changed code in natural language. We present a commit to illustrate each component in Figure 1. The upper rectangle contains the content of the commit message, which summarizes this commit in natural language (e.g., “Bugfix: Pass threshold to binarizer”). The lower rectangle is the changed code namely one chunk, which contains the file path (i.e., “tpot/tpot.py”) and the modified code from line 1025 to line 1031. The first line in this chunk starting with “@@” consists of the start line number (i.e., 1025) in the file, the total line statements (i.e., 7) and the function name (i.e., “_binarizer”). The changed code in this chunk is marked with “+” in the updated version of the code. Its previous version is marked with “-”. The remaining content is the context around the changed code to reveal its contextual information. Hence, in summary, for this commit in Figure 1, we can obtain that there is one line of code at line 1028 in the file of “tpot.py” changing the statement from “...copy=False)” to “...copy=False, threshold=threshold)”. The other statements (i.e. from line 1025 to 1027 and from line 1029 to 1031) are the context of the statement at line 1028. Note that we just utilize a simple commit, which only has one chunk with single-line statement modification as the example for better illustration. In some cases, a commit may only have the updated statements or the deleted statements. They may not

*All the code and data are available at https://anonymous.4open.science/r/CommitBart-443E
Return input_df.copy()

# The binarizer must be fit on only the training data

binarizer = Binarizer(copy=False, threshold=threshold)

binarizer.fit(train_features.values.astype(np.float64))

binarizer.transform(input_df.drop(['class', 'group', 'guess'], axis=1).values.astype(np.float64))

Figure 1: A commit with its commit id dbec56.

Table 1: The statistics of our collected commit benchmark.

| Benchmark       | C     | CSharp | Java | JavaScript | PHP   | Python | Typescript | Total   |
|-----------------|-------|--------|------|------------|-------|--------|------------|---------|
| Pre-train       | 1,971,109 | 660,587 | 935,151 | 986,669 | 1,148,074 | 1,029,676 | 762,760 | 7,440,026 |
| Fine-tune       | 71,924  | 61,902  | 81,126 | 87,064    | 99,230  | 89,502  | 67,762     | 558,510 |
| Total           | 1,989,033 | 722,489 | 1,016,277 | 1,073,733 | 1,247,304 | 111,9178  | 830,522 | 7,998,536 |

3 A Large-scale Benchmark for Commits

Different from automated code review (Li et al., 2022; Tufano et al., 2022, 2021), which aims to review the code quality from GitHub pull requests, we target at GitHub commits and propose a large pre-trained model for commits to support commit-related intelligent tasks. The existing benchmark from CommitBERT (Jung, 2021) only contains 345K commits which are far from the requirements for pre-training. To address this limitation, we collect a large-scale benchmark for commits instead. Specifically, we collect commits from the open-source projects on GitHub across 7 programming languages (i.e., C, CSharp, Java, JavaScript, PHP, Python, Typescript). To ensure the quality of the collected commits, we only keep the project whose description is in English and further select the top 500 projects based on their star ranking from January 2010 to December 2021 for each programming language through GitHub API \(^1\). Given a cloned project, we utilize the open-source tool GitPython \(^2\) to obtain the raw commits. These commits where the commit messages are non-English or the changed code length is greater than 2,000 are removed to reduce the sequence length. Furthermore, to ensure the quality of the commit message, followed by existing works (Jiang et al., 2017; Liu et al., 2020; Jung, 2021), we only fetch the first sentence in the commit message as the target and filter out these commits where the target length less than three. To alleviate the learning process of the model overfit to the duplicated samples (Allamanis, 2019), we conduct a strict de-duplication process to remove the same samples. Finally, we obtain over 7.99 million commits over 7 programming languages. For these 7.99 million commits, we

\(^{1}\) https://docs.github.com/en/rest

\(^{2}\) https://gitpython.readthedocs.io
further split them into pre-training data and fine-tuning data based on the “project”. We just select those projects which have less than 2,000 commits to construct the fine-tuning dataset. The detailed statistics of our collected benchmark are presented in Table 1.

4 CommitBART

4.1 Model Architecture

CommitBART follows the architecture of BART (Lewis et al., 2019) and we adopt the parameters of PLBART (Ahmad et al., 2021) to accelerate the training process. Since a commit usually consists of multiple different components such as the commit message, the updated code statements marked with “+”, and the deleted code statements marked with “-” and their context statements. To distinguish each component, we introduce some additional segment identifiers. Specifically, we define the identifier “[MSG]” at the start of a commit message $M = \{m_0, m_1, ..., m_t\}$ and “[FILE]” for file path $F = \{f_0, f_1, ..., f_j\}$ where $i$ and $j$ denote the number of $M$ and $F$ word tokens respectively. Similarly, we also define the identifier “[CODE]” at the start of the code to distinguish it from the message and file path. In addition, to distinguish the deleted code statements and the updated statements, we further add the identifiers (“[NEG]”/“[END]”) and (“[POS]”/“[END]”) between the start and end of these deleted/updated statements for distinction. Hence, generally, the code in the commit can be represented as follows:

$$C = \{c_0...[NEG]n_i...[END][POS]p_j...[END]c_k...
\{NEG\}n_i'...[END][POS]p_j'...[END]c_k'\}$$

where $c$ denotes the context statement and $c_0$ is the first token in $c$. Furthermore, $n_i/n_i'$ and $p_j/p_j'$ are the deleted and updated code statements respectively. We utilize segment embedding to embed these segments to ensure the model understands and incorporates information well. Hence, the input embedding representation for the model is constructed by summing the corresponding token, segment and positional embeddings.

4.2 Pre-training Tasks

Apart from text infilling (Lewis et al., 2019), we design other five pre-training tasks for commits to pre-train the model and these tasks can be divided into three categories. We use the example from Figure 1 for illustration. Specifically, the denoising and cross-modal generation tasks are presented in Figure 2, and the contrastive pre-training tasks are presented in Figure 3.

4.2.1 Denoising Objectives

Denoising pre-training, which aims at generating the original sequence given the noisy input, is an effective technique for pre-training encoder-decoder models (Lewis et al., 2019; Raffel et al., 2020). We also use it to pre-train CommitBART. Specifically, we apply a noisy function $N$ to the input sequence $X = ([CLS][MSG]M[F][CODE]C')$ to get the noisy input defined as $N(X)$, where the noisy function is to corrupt the input sequence by some strategies such as token masking, tokens infilling. The learning process is to ask the model to recover the original sequence from the noisy input and the loss function can be calculated as follows:

$$L_{Denoise}(\theta) = \sum_{t=1}^{[X]} -\log P_{\theta}(X_t | X_{<t}, N(X))$$ (1)

where $P$ is a generator that generates the $t$-th token given the noisy input $N(X)$, the original sequence before $t$ (i.e., $X_{<t}$) and the model parameters $\theta$. We adopted two strategies to corrupt the semantics of the input sequence (i.e., $X$).

Text Infilling. It randomly masks spans with a single masked token “[MASK]”. Then we ask the model to recover the original sequence. Specifically, we set the corruption rate as 15% in the input sequence and ensure the average span length to 3, followed by a Poisson distribution (Lewis et al., 2019). An example is illustrated in Figure 2 (a).

Graph-guided Token Masking (GTM). Since the input sequence $X$ consists of different components (i.e., commit message, changed code) and they may share some same tokens. Although text infilling helps the model learn better token representations, to further enhance the model in capturing the relations between different components in a commit, we introduce a graph-guided token masking task. A simple example is shown in Figure 2 (b). Specifically, by our preliminary observation, we find that there are some critical tokens (e.g., variable names, keywords, file names) that may be shared in commit message $M$ and changed code $C$. Hence, to enhance the semantic mapping, we construct a commit-graph, which links shared tokens between the commit message $M$, file path $F$ and changed code $C$. Then we randomly mask half
4.2.2 Cross-Modal Generation

Although denoising objectives ensure that the model learns better token representations, the existing code pre-trained models (Wang et al., 2021c; Guo et al., 2022) have proved that bimodal generation helps the decoder generate high-quality text output. Hence, we also design two bidirectional conversion generation tasks for GitHub commits to improve the model in generating the natural language text or the code. We formulate both cross-modal generation tasks as follows:

$$\mathcal{L}_{\text{Gen}}(\theta) = \sum_{t=1}^{|Y|} - \log p_{\theta}(Y_{t} | Y_{<t}, X_{\text{Gen}})$$  \hspace{1cm} (2)$$

where $X_{\text{Gen}}$ is the input sequence and $Y$ is the target sequence for generation.

**PL2NL Generation.** As shown in Figure 2 (c), this task takes the changed code (i.e. $X_{\text{Gen}} = \{[\text{CLS}]|\text{FILE}||F|\text{CODE}|\text{C}\}$) as input and requires the model to generate its corresponding commit message $Y = M$ to ensure model produce high-quality natural language texts for downstream natural language generation tasks.

**PLNL2PL Generation.** This task aims to generate the updated code snippet based on its commit message and the previous version of the code snippet. Specifically, the previous code snippet before the modification can be expressed as $C^{-} = \{c_{0}...[\text{NEG}]|n_{j}^\prime|...[\text{END}]...c_{l}\}$. Hence, the input sequence for this task can be expressed as $X_{\text{Gen}} = \{[\text{CLS}]|\text{MSG}|\text{FILE}|F|\text{CODE}|C^{-}\}$. The output $Y = \{c_{0}...[\text{POS}]|p_{0}^\prime|...[\text{END}]...c_{l}\}$, which is the updated code snippet for the model to generate. We incorporate this task to improve the model in generating better code snippets for downstream code generation tasks.

4.2.3 Contrastive Learning

The previous work (Jain et al., 2020) has confirmed that the robustness of code pre-trained models can be enhanced by contrastive learning, we also incorporate it into pre-train CommitBART. Generally, it aggregates the similar sequence representation (i.e., $\tilde{h}_{i}^{+}$) while pushing away dissimilar representations after encoding the input to an encoder. The loss function is:

$$\mathcal{L}_{\text{Contra}}(\theta) = \sum_{i=0}^{b-1} \log \frac{e^{\cos(\tilde{h}_{i}, \tilde{h}_{i}^{+})/\tau}}{\sum_{j=0}^{b-1} e^{\cos(\tilde{h}_{i}, \tilde{h}_{j})/\tau}} \hspace{1cm} (3)$$

where $b$ is batch size, $\tau$ is a temperature hyper-parameter (Wu et al., 2018) and $\cos(*)$ is the cosine similarity between two vector representations. Specifically, we design two kinds of contrastive strategies for commits.

**NLPL Alignment.** As shown in Figure 3 (a),
We select one understanding task (i.e., security patch identification) as fine-tuning tasks. We transfer CommitBART to commit-related tasks we directly feed the source sequence to the encoder with different dropout mask to CommitBART.

| Model                  | Acc   | Pre   | Rec   | F1    |
|------------------------|-------|-------|-------|-------|
| E-SPI                  | 92.81 | 83.03 | 90.43 | 89.40 |
| CodeBERT               | 93.28 | 98.77 | 90.33 | 92.18 |
| PLBART                 | 93.46 | 93.03 | 95.56 | 94.02 |
| CodeTS-base            | 93.66 | 93.03 | 95.56 | 94.02 |
| UniCoder               | 93.66 | 93.03 | 95.56 | 94.02 |
| Incr PLBART            | 93.06 | 93.07 | 95.47 | 94.26 |
| CommitBART             | 95.25 | 94.93 | 96.06 | 95.49 |
| w/o SIMCSE             | 95.18 | 94.88 | 95.22 | 95.06 |
| w/o PLNL2PL            | 95.40 | 94.11 | 95.46 | 94.78 |
| w/o PLNL/ALignt        | 95.75 | 95.38 | 96.98 | 95.75 |
| w/o SimCSE             | 95.19 | 96.12 | 94.76 | 95.44 |

Table 2: Results of security patch identification, where * marks the values from Wu et al. (Wu et al., 2022).

5.3 Fine-tuning

We transfer CommitBART to commit-related tasks at fine-tuning phase. Generally, fine-tuning tasks can be categorized into two classes: understanding tasks and generation tasks. For understanding tasks, we directly feed the source sequence to the encoder and ask the decoder to generate its predicted label. For generation tasks, CommitBART can be naturally adapted with its encoder-decoder framework to different commit-related generation tasks.

5. Experimental Setup

In this section, we first introduce the evaluation tasks and then introduce the compared baselines. The details of pre-training and fine-tuning settings can be found in Appendix A and Appendix B.

5.1 Evaluation Tasks

We select one understanding task (i.e., security patch identification) and three generation tasks (i.e., commit message generation, positive code statements generation, and updated code snippet generation) as fine-tuning tasks.

Security Patch Identification. This task aims to identify whether a commit fixes a software vulnerability or not. It has been extensively researched with some neural models (e.g., SPI (Zhou et al., 2021b), E-SPI (Wu et al., 2022), PatchRNN (Wang et al., 2021b)). We use the same dataset provided by E-SPI (Wu et al., 2022) with the same train-validation-test split for evaluation.

Commit Message Generation. This task targets generating a commit message to summarize the changed code in natural language. Apart from evaluating the widely used open-source dataset ATOM (Liu et al., 2020) for Java programming language, we also used the constructed fine-tuning dataset from our benchmark (See Table 1) across 7 languages for evaluation. We split the data into train/validation/test based on “project” to evaluate. Followed by Tao et al. (Tao et al., 2021), we use smoothed BLEU-4 as the evaluation metric.

Positive Code Statements Generation. We propose this new commit-related task, which targets generating positive statements marked by “+”, that takes the commit message, and file path with the code snippet before modification as input. We only consider the commits that have consecutive statement modifications for evaluation. Specifically, if a commit in our constructed fine-tuning dataset from Table 1 has multiple non-consecutive modifications (a simple example is shown in Appendix Figure 8a), which removes two non-consecutive lines of statements, we remove these samples. This task is similar to source code edit (Chakraborty and Ray, 2021). Compared with it, which generated patched code statements based on buggy code statements, ours aim to generate updated code statements from the previous version of code statements.

Updated Code Snippet Generation. We further propose a more challenging task that requires the model to generate the completed updated code snippet. Different from positive code statements generation, this task needs to locate the position of the updated statements first and then generate the completed code snippet. We include these commits that have multiple inconsecutive modifications (see an example in Appendix Figure 8a). This task is valuable for software developers to generate the code that meets the requirement based on the previous version of code as well as the demand in natural language. We use our fine-tuning dataset in Table 1 for evaluation.

The statistics of the used datasets for these fine-
Table 3: Smoothed BLEU-4 scores on the commit message generation task. The “Overall” column presents the average score over seven programming languages and “ATOM” represents experimental results on ATOM dataset.

| Model        | C    | CSharp | Java | JavaScript | PHP | Python | Typescript | Overall | ATOM |
|--------------|------|--------|------|------------|-----|--------|------------|---------|------|
| Transformer  | 9.75 | 12.79  | 15.14| 14.45      | 8.80| 13.19  | 20.55      | 18.04   | 10.14|
| PLBART       | 11.23| 15.61  | 15.85| 15.96      | 11.02|14.89   | 21.60      | 15.17   | 12.35|
| CodeTS-base  | 13.74| 18.82  | 20.05| 19.63      | 12.01|18.55   | 23.49      | 18.04   | 13.17|
| UniXcoder    | 13.02| 18.40  | 20.22| 20.70      | 12.20|17.63   | 23.63      | 17.97   | 13.06|
| Incr-PLBART  | 11.98| 16.38  | 16.55| 17.33      | 11.25|15.10   | 21.95      | 15.79   | 13.24|
| CommitBART   | 15.99| 21.26  | 22.00| 25.96      | 13.93|19.50   | 24.86      | 20.60   | 17.85|
| - w/o SEG    | 15.65| 21.17  | 22.25| 26.10      | 13.38|19.08   | 23.17      | 20.11   | 16.94|
| - w/o GTM    | 17.05| 23.00  | 22.92| 22.97      | 17.37|19.17   | 23.10      | 20.14   | 16.97|
| - w/o PL2NL  | 14.31| 16.66  | 20.23| 22.97      | 17.37|19.60   | 23.08      | 17.25   | 17.62|
| - w/o PLNL2PL| 15.86| 21.51  | 22.91| 26.97      | 13.29|19.40   | 22.20      | 20.31   | 16.13|
| - w/o NLPLalign | 15.94| 20.67  | 22.53| 26.63      | 12.87|19.75   | 22.98      | 20.70   | 17.13|
| - w/o SimCSE | 15.95| 20.67  | 22.54| 26.85      | 13.62|19.11   | 23.06      | 20.26   | 17.28|

5.2 Baselines

For the understanding task of security patch identification, since we use the dataset from E-SPI (Wu et al., 2022) with the same train-validation-test split, we directly report the best results from their paper as one of our baselines. For generation tasks, we add one supervised baseline Transformer model (Vaswani et al., 2017), which is trained on fine-tuning commit dataset without pre-training to verify the effectiveness of pre-training techniques. Furthermore, we compare CommitBART with four state-of-the-art pre-trained models for code (i.e., CodeBERT (Feng et al., 2020), PLBART (Ahmad et al., 2021), CodeT5-base (Wang et al., 2021c) and UniXcoder (Guo et al., 2022)), which are trained on a large corpus of code functions to validate the effectiveness of utilizing commit data to pretrain a model for commit-related tasks. We directly employ these released pre-trained models with default configurations for comparison. In addition, since our model adopts the parameters of PLBART, which is trained by text infilling, to validate the effectiveness of other designed pre-training tasks in CommitBART, we further add one baseline Incr-PLBART and it is incrementally trained from PLBART on our collected commit benchmark using text infilling.

6 Experimental Results and Analysis

In this section, we present the experimental results with the analysis.

6.1 Compared with Baselines

We compare the results of these evaluation tasks with the baselines in Table 2, Table 3, Table 4 and Table 5 respectively. We can conclude the following findings: 1) Compared with the supervised techniques such as Transformer, the pre-trained models improve the performance significantly over these tasks. 2) Compared with the pre-trained models in code, CommitBART outperforms them, especially on the generation tasks significantly. We attribute the improvements to the used large amount of commit data. Specifically, we utilize over 7 million commits to pre-train a commit-related model for downstream commit-related tasks and this model is domain-specific. 3) Compared with Incr-PLBART, our improvements are also significant, which confirms that except for text infilling, the other pre-training tasks in CommitBART are also beneficial for the improvements.

6.2 Model Analysis

We further conduct an ablation study to investigate each pre-training task to the final performance across these fine-tuning tasks and the results are reported in the last line of Table 2, Table 3, Table 4 and Table 5 respectively. Through analysing the results, we have the following findings: 1) Segment embedding is useful in CommitBART, although it is not widely used in code pre-trained models. We believe it is due to commits usually having more complex components (e.g., commit message, deleted/updated statements), hence segment embedding helps the model incorporate each component well. 2) Two cross-modal generation tasks (i.e., PL2NL and PLNL2PL) provide significant improvements to the generation tasks. Taking the updated code snippet generation task in Table 5 as an example, after removing PLNL2PL, the overall BLEU-4 score drops from 57.63 to 53.70 across 7 programming languages. 3) Apart from the cross-modal generation tasks, graph-guided token masking (GTM) is more critical than the remaining tasks on three generation tasks. It demonstrates that by constructing a commit-graph to predict the masked nodes by their connected nodes in the graph, the semantic gap between the message (NL) and changed
@def write_version_py(filename=None):

tests_require=['mock >= 1.0.1', 'nose >= 1.0']

UniXcoder: Add xraypackage to setup.py

Incr-PLBART: Add xraypackage to setup.py

CodeT5-base: Fix variable.values

"xray.backends"). In contrast, CommitBART generates the accurate package name and the generated output is the same as the ground-truth. We attribute to the designed graph-guided token masking pre-training task, which helps the model capture the critical semantic information in a commit.

6.3 Case Study

We also conduct a case study including an example from commit message generation with the generated results from different models to intuitively demonstrate the effectiveness of CommitBART. It is shown in Figure 4 and more examples of different models for these commit-related generation tasks can be found in Appendix C. From the changed code in this example, we find that this commit is to add a package namely “xray.backends”. Its commit message (i.e., ground-truth) “Add xray.backends to setup.py” further confirms it. The results produced by UniXcoder and Incr-PLBART are better than other baselines. However, both models fail to generate the accurate package name (i.e., “xray.backends”). In contrast, CommitBART generates the accurate package name and the generated output is the same as the ground-truth. We attribute to the designed graph-guided token masking pre-training task, which helps the model capture the critical semantic information in a commit.

7 Conclusion

Due to the lack of large-scale commit data, we first collect a benchmark (over 7.99 million commits) across 7 programming languages and make it public for follow-up researchers. Based on this benchmark, we present CommitBART, a pre-trained encoder-decoder model for GitHub commits. The model is pre-trained via three categories (i.e., denoising objectives, cross-modal generation and con-
trastive learning) for six pre-training tasks to learn commit representations. We are the first to present a large pre-trained model for GitHub commits and further, unify a “commit intelligence” framework with one commit-related understanding task and three generation tasks. Extensive experiments confirm CommitBART significantly outperforms previous works on these tasks. Further ablation study also reveals the effectiveness of each pre-training task. We encourage more commit-related tasks to merge into our framework.

8 Limitations

While CommitBART is able to achieve superior performance for different code-related tasks. We claim that it still has the following limitations: First, for the downstream task of updated code snippet generation, we just use BLEU-4 and exact match as the evaluation metrics. However, recent studies (Chen et al., 2021) have proved the deficiencies in match-based metrics such as BLEU for code and further proposed the execution-based metric (i.e., pass@k) to evaluate the functional correctness of the generated code. Although pass@k can be used for the testset (i.e., HumanEval (Chen et al., 2021)), which evaluates the correctness of the generated code based on the test cases, this operation of designing test cases for the task of updated code snippet are not applicable because these generated code snippets from the previous version of code are complex and they cannot compile without the well-configured operating environment.

Second, we just select the first sentence as the target for commit message. It will lose some useful information in some cases where the left sentences are also important to this changed code. We extract the first sentence so that we can accelerate the training and inference process.

References

Wasi Uddin Ahmad, Saikat Chakraborty, Baishakhi Ray, and Kai-Wei Chang. 2021. Unified pre-training for program understanding and generation. arXiv preprint arXiv:2103.06333.

Miltiadis Allamanis. 2019. The adverse effects of code duplication in machine learning models of code. In Proceedings of the 2019 ACM SIGPLAN International Symposium on New Ideas, New Paradigms, and Reflections on Programming and Software, pages 143–153.

Luca Buratti, Saurabh Pujar, Mihaela Bornea, Scott McCarley, Yanhui Zheng, Gaetano Rossiello, Alessandro Morari, Jim Laredo, Veronika Thost, Yufan Zhuang, et al. 2020. Exploring software naturalness through neural language models. arXiv preprint arXiv:2006.12641.

Saikat Chakraborty and Baishakhi Ray. 2021. On multi-modal learning of editing source code. In 2021 36th IEEE/ACM International Conference on Automated Software Engineering (ASE), pages 443–455. IEEE.

Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde de Oliveira Pinto, Jared Kaplan, Harri Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, et al. 2021. Evaluating large language models trained on code. arXiv preprint arXiv:2107.03574.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2019, Minneapolis, MN, USA, June 2-7, 2019, Volume 1 (Long and Short Papers), pages 4171–4186. Association for Computational Linguistics.

Zhangyin Feng, Daya Guo, Duyu Tang, Nan Duan, Xiaocheng Feng, Ming Gong, Linjun Shou, Bing Qin, Ting Liu, Daxin Jiang, et al. 2020. Codebert: A pre-trained model for programming and natural languages. arXiv preprint arXiv:2002.08155.

Tianyu Gao, Xingcheng Yao, and Danqi Chen. 2021. Simcse: Simple contrastive learning of sentence embeddings. arXiv preprint arXiv:2104.08821.

Daya Guo, Shuai Li, Nan Duan, Yanlin Wang, Ming Zhou, and Jian Yin. 2022. Unixcoder: Unified cross-modal pre-training for code representation. arXiv preprint arXiv:2203.03850.

Daya Guo, Shuo Ren, Shuai Li, Zhangyin Feng, Duyu Tang, Shujie Liu, Long Zhou, Nan Duan, Alexey Svyatkovskiy, Shengyu Fu, et al. 2020. Graphcodebert: Pre-training code representations with data flow. arXiv preprint arXiv:2009.08366.

Paras Jain, Ajay Jain, Tianjun Zhang, Pieter Abbeel, Joseph E Gonzalez, and Ion Stoica. 2020. Contrastive code representation learning. arXiv preprint arXiv:2007.04973.

Siyuan Jiang, Ameer Armaly, and Collin McMillan. 2017. Automatically generating commit messages from diffs using neural machine translation. In 2017 32nd IEEE/ACM International Conference on Automated Software Engineering (ASE), pages 135–146. IEEE.

Xue Jiang, Zhuoran Zheng, Chen Lyu, Liang Li, and Lei Lyu. 2021. Treebert: A tree-based pre-trained model for programming language. In Proceedings
of the Thirty-Seventh Conference on Uncertainty in Artificial Intelligence, UAI 2021, Virtual Event, 27-30 July 2021, volume 161 of Proceedings of Machine Learning Research, pages 54–63. AUAI Press.

Tae-Hwan Jung. 2021. Commitbert: Commit message generation using pre-trained programming language model. arXiv preprint arXiv:2105.14242.

Aditya Kanade, Petros Maniatis, Gogul Balakrishnan, and Kensen Shi. 2020. Pre-trained contextual embedding of source code. CoRR, abs/2001.00059.

Mike Lewis, Yinhan Liu, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Ves Stoyanov, and Luke Zettlemoyer. 2019. Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. arXiv preprint arXiv:1910.13461.

Zhili Li, Shuai Lu, Daya Guo, Nan Duan, Shailesh Jannu, Grant Jenks, Deep Majumder, Jared Green, Alexey Svyatkovskiy, Shengyu Fu, et al. 2022. Automating code review activities by large-scale pre-training. In Proceedings of the 30th ACM Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering, pages 1035–1047.

Shangqing Liu, Cuiyun Gao, Sen Chen, Nie Lun Yu, and Yang Liu. 2020. Atom: Commit message generation based on abstract syntax tree and hybrid ranking. IEEE Transactions on Software Engineering.

Shuai Lu, Daya Guo, Shuo Ren, Junjie Huang, Alexey Svyatkovskiy, Ambrosio Blanco, Colin B. Clement, Dawn Drain, Daxin Jiang, Duyu Tang, Ge Li, Lidong Zhou, Linjun Shou, Long Zhou, Michele Tufano, Ming Gong, Ming Zhou, Nan Duan, Neel Sundaresan, Shao Kun Deng, Shengyu Fu, and Shujie Liu. 2021. Codexglue: A machine learning benchmark dataset for code understanding and generation. In Proceedings of the Neural Information Processing Systems Track on Datasets and Benchmarks 1, NeurIPS Datasets and Benchmarks 2021, December 2021, virtual.

Changan Niu, Chuanyi Li, Vincent Ng, Jidong Ge, Liguo Huang, and Bin Luo. 2022. Spt-code: Sequence-to-sequence pre-training for learning the representation of source code. arXiv preprint arXiv:2201.01549.

Alec Radford, Jeffrey Wu, Rewon Child, David Lan, Dario Amodei, Ilya Sutskever, et al. 2019. Language models are unsupervised multitask learners. OpenAI blog, 1(8):9.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, Peter J Liu, et al. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. J. Mach. Learn. Res., 21(140):1–67.

Alexey Svyatkovskiy, Shao Kun Deng, Shengyu Fu, and Neel Sundaresan. 2020. Intellcode compose: code generation using transformer. In ESEC/FSE ’20: 28th ACM Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering, Virtual Event, USA, November 8-13, 2020, pages 1433–1443. ACM.

Wei Tao, Yanlin Wang, Ensheng Shi, Lun Du, Shi Han, Hongyu Zhang, Dongmei Zhang, and Wenqiang Zhang. 2021. On the evaluation of commit message generation models: an experimental study. In 2021 IEEE International Conference on Software Maintenance and Evolution (ICSME), pages 126–136. IEEE.

Rosalia Tufano, Simone Masropalo, Luca Pascarella, Denys Poshyvanyk, and Gabriele Bavota. 2022. Towards automating code review activities. In 2021 IEEE/ACM 43rd International Conference on Software Engineering (ICSE), pages 163–174. IEEE.

Ashish Vaswani, Noam Shazeer, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4-9, 2017, Long Beach, CA, USA, pages 5998–6008.

Xin Wang, Yasheng Wang, Fei Mi, Pingyi Zhou, Yao Wan, Xiao Liu, Li Li, Hao Wu, Jin Liu, and Xin Jiang. 2021a. Syncobert: Syntax-guided multimodal contrastive pre-training for code representation. arXiv preprint arXiv:2108.04556.

Xinda Wang, Shu Wang, Pengbin Feng, Kun Sun, Sushil Jajodia, Sanee Benchaaboun, and Frank Geck. 2021b. Patchrnn: A deep learning-based system for security patch identification. In MILCOM 2021-2021 IEEE Military Communications Conference (MILCOM), pages 595–600. IEEE.

Yue Wang, Weishi Wang, Shafiq Joty, and Steven CH Hoi. 2021c. Codet5: Identifier-aware unified pre-trained encoder-decoder models for code understanding and generation. arXiv preprint arXiv:2109.00859.

Bozhi Wu, Shangqing Liu, Ruitao Feng, Xiaofei Xie, Jingkai Siow, and Shang-Wei Lin. 2022. Enhancing security patch identification by capturing structures in commits. arXiv preprint arXiv:2207.00022.

Zhirong Wu, Yuanjun Xiong, Stella X Yu, and Dahua Lin. 2018. Unsupervised feature learning via non-parametric instance discrimination. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 3733–3742.
We follow the architecture of BART (Lewis et al., 2019), which is made up of a 6-layer Transformer encoder and a 6-layer decoder with the dimension of 768 and 12 heads (∼140M parameters). We adopt the parameters of PLBART (Ahmad et al., 2021) to initialize the pre-trained model and add an additional segment embedding layer to encode different segment identifiers. We also adopt the vocabulary set of PLBART, which contains 50K subtokens and further add 5 different segment identifiers into the vocabulary set to represent different components in a commit. We set the maximum input sequence length to 512 and use the mixed precision of FP16 to accelerate the pre-training process. We set the batch size to 512 and employ the AdamW optimizer to update the model parameters with a learning rate of 2e-4. We pre-train the model on one DGX server, which has 8 NVIDIA Tesla V100 with 32GB memory. The total steps are set to 80K where the categories of denoising objectives, cross-modal generation and contrastive learning take up 60%, 30%, and 10% respectively. One category has two different pre-training tasks and each of them accounts for half of the steps. The total time for the pre-training process is about 60 hours. We follow Guo et al. (Guo et al., 2020) to sample each batch from the same programming language according to a distribution \( \{q_i\}_{i=1}^N \), where \( n_i \) is the number of examples for \( i \)-th programming language and \( \alpha = 0.7 \) to alleviate the bias towards high-resource languages.

\[
q_i = \frac{p_i^\alpha}{\sum_{j=1}^N p_j^\alpha}, \quad p_i = \frac{n_i}{\sum_{k=1}^N n_k}
\]  

### A Pre-training Settings

We follow the architecture of BART (Lewis et al., 2019), which is made up of a 6-layer Transformer encoder and a 6-layer decoder with the dimension of 768 and 12 heads (∼140M parameters). We adopt the parameters of PLBART (Ahmad et al., 2021) to initialize the pre-trained model and add an additional segment embedding layer to encode different segment identifiers. We also adopt the vocabulary set of PLBART, which contains 50K subtokens and further add 5 different segment identifiers into the vocabulary set to represent different components in a commit. We set the maximum input sequence length to 512 and use the mixed precision of FP16 to accelerate the pre-training process. We set the batch size to 512 and employ the AdamW optimizer to update the model parameters with a learning rate of 2e-4. We pre-train the model on one DGX server, which has 8 NVIDIA Tesla V100 with 32GB memory. The total steps are set to 80K where the categories of denoising objectives, cross-modal generation and contrastive learning take up 60%, 30%, and 10% respectively. One category has two different pre-training tasks and each of them accounts for half of the steps. The total time for the pre-training process is about 60 hours. We follow Guo et al. (Guo et al., 2020) to sample each batch from the same programming language according to a distribution \( \{q_i\}_{i=1}^N \), where \( n_i \) is the number of examples for \( i \)-th programming language and \( \alpha = 0.7 \) to alleviate the bias towards high-resource languages.

\[
q_i = \frac{p_i^\alpha}{\sum_{j=1}^N p_j^\alpha}, \quad p_i = \frac{n_i}{\sum_{k=1}^N n_k}
\]  

### B Fine-tuning Settings

#### B.1 Understanding Task

For the understanding task of security patch identification, we directly utilize the released dataset from Wu et al. (Wu et al., 2022), which consists of 26500 training samples, 3301 validation samples and 3294 test samples for evaluation. We employ AdamW optimizer to fine-tune CommitBART with a 5e-5 learning rate and the batch size 32 for 4K steps. We set the maximum input sequence length to 512 and the target sequence length to 5, which includes the start token “[CLS]”, the task prefix “security patch”, the label “True” or “False” and the end token “[EOS]”.

#### B.2 Generation Tasks

For the generation task of commit message generation, apart from the dataset used in ATOM (Liu et al., 2020), we also utilize the fine-tuning dataset from our benchmark (See Table 1). Specifically, we split it into train/validation/testset based on the “project” with a ratio of 75%:10%:15% for evaluation. For the task of updated code snippet generation, we also use this divided data for evaluation. For the task of positive code statements generation, we also use this divided data for evaluation. The statistics of the train, validation and test are shown in Table 6. For each task, we utilize AdamW optimizer to fine-tune CommitBART with a 5e-5 learning rate of batch size 32 for 10K steps. Furthermore, we set the early stop based on the validation loss. The maximum input sequence length is set to 512 for these tasks, while the target sequence is set to 150 for commit message generation, 512 for updated code snippet generation and 300 for positive code statements generation respectively.
Table 6: The statistics of the fine-tuning dataset for commit message generation, updated code snippet generation and positive code statements generation. The first row is the dataset used for the first two tasks while second row is the dataset for the last task.

| Fine-tune  | C       | CSharp   | Java    | JavaScript | PHP    | Python  | Typescript | Total   |
|------------|---------|----------|---------|------------|--------|---------|------------|---------|
| Train      | 51,504  | 45,425   | 63,189  | 68,338     | 78,450 | 70,137  | 51,526     | 428,569 |
| Validation | 8,902   | 5,501    | 7,512   | 8,100      | 9,239  | 8,326   | 6,172      | 53,752  |
| Test       | 11,518  | 10,976   | 10,425  | 10,626     | 11,541 | 11,039  | 10,064     | 76,189  |
| Positive-Train | 20,746 | 19,726   | 27,619  | 31,809     | 35,015 | 31,809  | 28,198     | 189,438 |
| Positive-Validation | 2,320  | 2,562    | 2,580   | 2,655      | 2,490  | 2,364   | 2,957      | 17,926  |
| Positive-Test    | 2,321  | 2,562    | 2,580   | 2,656      | 2,491  | 2,364   | 2,958      | 17,932  |

File: *pac4j-mongo/src/main/java/org/pac4j/mongo/credentials/authenticator/MongoAuthenticator.java*

**Message:** Check adapter before initialization

**Previous Code Snippet:**
```java
@@ public ViewGroup getTopView() {
    public void setElevationEnabled(boolean elevationEnabled) {
        this.elevationEnabled = elevationEnabled;
        - init(false);
    }
}
```

**Ground Truth:** if (adapter != null) { init(false); }

**CodeBERT:** if (false) { init(false); }

**PLBART:** if (!this.isInitialized()) { init(false); }

**UniXcoder:** init(true);

**Incr-PLBART:** if (false) { init(false); }

**CommitBART:** if (adapter != null) { init(false); }

(a) The commit id is 054122.

File: *Library/src/main/java/com/liulishuo/filedownloader/services/DownloadMgrInitialParams.java*

**Message:** fix: fix the fatal crash when you don’t provide the init-params for customize component

**Previous Code Snippet:**
```java
@@ public DownloadMgrInitialParams() {
    public DownloadMgrInitialParams(InitCustomMaker maker) {
        this.mMaker = maker;
        - maker.securityCheck();
        } public int getMaxNetworkThreadCount() {
```

**Ground Truth:** if (maker != null) { maker.securityCheck(); }

**CodeBERT:** maker.securityCheck();

**PLBART:** maker.securityCheck(false);

**CodeT5-base:** if (!maker.isSecurityCheckEnabled()) (maker.securityCheck());

**UniXcoder:** maker.securityCheck();

**Incr-PLBART:** maker.securityCheck(true);

**CommitBART:** if (maker != null) { maker.securityCheck(); }

(b) The commit id is 99cfb9.

Figure 6: Two examples from Java for the task of positive code statements generation.

C Case Study

In this section, we provide more examples to demonstrate the effectiveness of CommitBART.

C.1 Commit Message Generation

We further provide one example of commit message generation. From Figure 5, we can see that its commit message is to delete an unused variable and the changed code is to delete the statement (i.e., “const bool is_gles = glext.version.is_es”). By comparing the results produced by different models, we find that CommitBART can generate a better result.

C.2 Positive Code Statements Generation

We provide two examples for the task of positive code statements generation in Figure 6a and Figure 6b respectively. The input consists of the file path, the commit message and the previous code snippet. We ask the model to generate the positive code statements marked as “+” in a commit. We can see that both commits aim to add a security check to avoid code crashes. Compared with the results produced by different models, CommitBART generates accurate positive code statements.

C.3 Updated Code Snippet Generation

We provide two examples for the task of updated code snippet generation. Similar to the task of positive code statements generation, the input includes the file path, the commit message and the previous code snippet. For the first example, the input is presented in Figure 7a and the ground-truth for this example is presented in Figure 7b. By Figure 7a, we can get that the updated code snippet needs to add a variable safety check to avoid “ph” as empty. The results produced by different models are presented in Figure 7c to Figure 7h accordingly. We can observe that PLBART and Incr-PLBART produce better results than other baseline models for this example, however, they both misunderstand the semantics of the commit message and produce the exact opposite results (i.e., “if (tPh.isEmpty())” and “if (tPh.length() == 0”)). In contrast, CommitBART can capture the semantics well and produce the same code snippet with the ground-truth.

For another example, which is shown in Figure 8,
we can see that this commit removes the variable “isContinuousIntegration” and further deletes its usage in the following statement. The modification is non-consecutive. The results produced by CodeBERT and CodeT5 only copy the original statements while the results produced by the remaining baselines remove the variable declaration, but fail to delete its usage. In contrast, CommitBART can produce the same code snippet with the ground-truth.
Figure 7: One example from Java for the task of updated code snippet generation where the commit id is 0aa027.
Figure 8: Another example from Java for the task of updated code snippet generation where the commit id is e640a3.
PLBART/UniXcoder/Incr-PLBART:

```java
public class IntegrationTestActiveProfilesResolver implements ActiveProfilesResolver {
    public String[] resolve(final Class<?> testClass) {
        final boolean isCI = Boolean.valueOf(System.getProperty("CI", "false"));
        final boolean isTravis = Boolean.valueOf(System.getProperty("TRAVIS", "false"));
        final String[] activeProfiles = new String[] {"ci"};
        if (isCI || isTravis) {
            activeProfiles = new String[1] {"ci"};
        } else {
            activeProfiles = new String[1] {"integration"};
        }
    }
}
```

(d) The results provided by PLBART, UniXcoder and Incr-PLBART.

CommitBART:

```java
public class IntegrationTestActiveProfilesResolver implements ActiveProfilesResolver {
    public String[] resolve(final Class<?> testClass) {
        final boolean isCI = Boolean.valueOf(System.getProperty("CI", "false"));
        final boolean isTravis = Boolean.valueOf(System.getProperty("TRAVIS", "false"));
        final String[] activeProfiles = new String[] {"ci"};
        if (isCI || isTravis) {
            activeProfiles = new String[1] {"ci"};
        } else {
            activeProfiles = new String[1] {"integration"};
        }
    }
}
```

(c) The result provided by CommitBART.

Figure 8: Another example from Java for the task of updated code snippet generation where the commit id is e640a3 (cont.).