
BigIssue: A Realistic Bug Localization Benchmark

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Abstract

As machine learning tools progress, the inevitable question arises: How can machine learning help us write better code? With significant progress being achieved in natural language processing with models like GPT-3 and Bert, the applications of natural language processing techniques to code are starting to be explored. Most of the research has been focused on automatic program repair (APR), and while the results on synthetic or highly filtered datasets are promising, such models are hard to apply in real-world scenarios because of inadequate bug localization. We propose BigIssue: a benchmark for realistic bug localization. The goal of the benchmark is two-fold. We provide (1) a general benchmark with a diversity of real and synthetic Java bugs and (2) a motivation to improve bug localization capabilities of models through attention to the full repository context. With the introduction of BigIssue, we hope to advance the state of the art in bug localization, in turn improving APR performance and increasing its applicability to the modern development cycle.

1 Introduction

Recent advances in natural language processing (NLP) [2] [5] [22] have increased interest in applying NLP techniques to code understanding. With the development of code encoders [9] [16], this task is becoming increasingly more accessible and appealing. As research has jumped ahead into the task of Automated Program Repair (APR), the results have been not been adequate. Although synthetic datasets have largely been solved (see Section 2.1), models have been surprisingly underperforming on real-world datasets, many not even able to repair a quarter of the bugs in the benchmark [24]. This is despite research suggesting that current APR benchmarks suffer from a lack of diversity [8]. As a consequence, many APR models are prone to overfitting to specific datasets [25]. Although interesting from an academic perspective, such tools would hardly be useful in a real industrial scenario.

We posit that the three major limitations to APR methods being used today are: (1) training to fix already located bugs rather than finding bugs and fixing them, (2) the inability of models to take large contexts into account, and (3) the reliance on information besides pure code. The first limitation is straightforward: patches have limited context outside of the lines immediately before and after each patch. It has been shown that APR performance improves significantly if a good fault localization algorithm is used to detect buggy code locations [8] [21]. The second limitation prevents models from finding bugs that depend on the context of the program. Even for human readers, many real-world bugs require a lot of program-specific context to be detectable. One of the most popular code

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encoders today [9] only supports encoding of sequences up to 512 tokens, not nearly enough to process most Java files in real-world programs (on average 7.5k tokens with the RoBERTa tokenizer [22]). The third limitation follows from the fact that the most common method for fault localization used today (SBFL) [14] is heavily reliant on test cases exposing potentially buggy locations (see Section 2.2).

In order to advance the state of the art of both BL and APR models, we introduce BigIssue. The major contributions of BigIssue include:

- A large collection of confirmed real-world bugs with line-level annotations. Each bug has been reported by live users to the GitHub Issues bug-tracking system and fixed via a commit or pull request. The dataset contains a total of 23,924 bugs sourced from 4,233 Java repositories.
- A very hard synthetic bug collection dataset. It is a long-sequence synthetic bug dataset, generated by InCoder [11], a state of the art perturbation generation model.
- An empirical demonstration of the hardness of the real benchmark as compared to a synthetic dataset. Even with advanced synthetic bug generation techniques the performance on real bugs will not be adequate, which calls for further research into realistic bug detection.

By providing a large and diverse dataset of synthetic and real bugs from a multitude of projects without any extra information outside of code, we hope to push the direction of research towards line-level long-context bug localization for better performance on APR tasks.

2 Prior Art

2.1 Automatic Program Repair

Since bug localization is fundamentally related to automatic program repair, we provide a brief survey of existing APR benchmarks and their drawbacks.

Real-world Benchmarks The `Defects4J` dataset [15] has been widely used in automatic program repair. It consists of 357 (835 in version 2) bugs sourced from 10 (100) top open-source Java projects. Bugs are manually reviewed and each bug has at least 1 test case that exposes the bug. APR methods, however, are not successful enough on this real dataset for the models to be useful in real-world applications. The most recent state-of-the-art model can only fix 67 out of 357 bugs [33], while the two previous state-of-the-art models could only fix 44 [24] and 57 [13] bugs. This is despite recent research that suggests APR methods are overperforming on `Defects4J` as compared to other similar benchmarks [8]. `Bugs.jar` [26] is a similar dataset but with an expanded scope of 8 popular projects from the Apache foundation.

Another widely used dataset is the `ManySStubs4J` dataset [17]. It's a collection of many "stupid" bugs mined from 100 (1,000) top open-source Java repositories. The collection includes only those changes where the change is a single line of code and falls into one of the pre-determined 16 categories of bugs. While convenient, it suffers from a lack of complicated bugs and highly selective criteria.

`Learning-fixes` [29] is a collection of about 58,350 short methods mined from GitHub. Each of the methods was semantically idiomized and presented in the benchmark. The main limitation of this dataset is that it's a method-level dataset: each bug should be identifiable and fixable based on the context only present in that particular method. For real bugs, this is usually not the case.

`DLFix` [20] is another dataset aimed at APR tasks. The dataset consists of almost 5 million methods, enhanced with metadata, and the corresponding fixed versions of the method for a particular repository. While interesting for limited cases, the method-level granularity as well as the necessity of building metadata for each method limits its usefulness, especially on longer methods.

Table 1 presents a comparison of some of the existing APR benchmarks.

Synthetic Benchmarks A natural way to deal with the lack of data diversity in current real-world benchmarks is to create synthetic benchmarks by perturbing code. Existing work accomplishes this either via a separate model [19] [6] [16] [32] or via a static oracle (such as a linter) [1]. While

Dataset	Size	Gran.	Bug Length	Context	# of Repos	Filters
BigIssue	23,924	Line	Multi-line	Repository	4233	No
	357					
Defects4J [15]	(835)	Line	Multi-line	Repository	5 (17)	No
Bugs.jar [26]	1158	Line	Multi-line	Repository	8	No
	10,231					
ManySStubs4J [17]	(63,923)	Line	Single-line	Repository	100 (1000)	Yes
iBugs [4]	369	Line	Multi-line	Repository	1	No
Learning-Fixes [29]	58,350	Line	Multi-line	Method	-	No
DLFix [20]	4,973,000	Method	Multi-line	Repository	8	No

Table 1: Comparison of Major Java Bug Detection Datasets.

attractive, there is significant evidence that good performance on these benchmarks does not translate to good performance on real-life bugs [8]. We also perform an experiment 5 that suggests that even good performance on sophisticated perturbation datasets does not translate well to fixing real bugs.

2.2 Using Existing Benchmarks for Bug Localization

Fault localization and fault prediction have been severely understudied. According to a recent survey [34] current fault localization and prediction methods can’t even localize half of the bugs in the Defects4J [15] dataset. The most widely used and best-performing method for fault localization is Spectrum-based fault localization (SBFL) [14]. While elementary and simple to implement, it relies heavily on the quality and quantity of test cases, especially for large programs [18]. The lack of scalability for this method motivates further research into the problem of bug localization.

3 BigIssue Synthetic Dataset

3.1 Motivation

Error localization in the context of automatic program repair has been a widely studied research topic [34] [8] [27] [28] [30]. Evaluation of approaches towards error localization requires the construction of a dataset with known ground-truth. One methodology to create such dataset is to consider existing code and introduce erroneous perturbations in the form of samples drawn from a generative model. In prior art [19], synthetic perturbations have been adopted on a function-level granularity with weak generative models such as small LSTMs. The underlying distribution of such synthetic dataset may be quite dissimilar to the distribution of realistic bugs, which occur in software engineering [8]. To decrease this discrepancy, in the following, we will advance this concept to file-level data and sample perturbations from a strong generative model.

To evaluate a means of error localization, one requires an evaluation dataset with known ground-truth errors. Our synthetic dataset adopts the methodology of gathering “real” code as observations and introducing synthetic perturbations in the observations. Here, the perturbation is in the form of a rewrite of the original sequence of code into a perturbed sequence of code. In our approach, a portion of the original code is “masked out” and a generative model is recruited to “fill in” the masked out code. The “filled in” portion of the code constitutes the synthetic perturbation. The perturbation of the original code is assumed to likely to contain “errors”.

While the above approach based on perturbations may appear obvious and trivial, the construction of such datasets is challenging. This is due to, (1) existing code is not guaranteed to be free of errors, (2) the definition or ontology of an “error” or “bug” itself is non-trivial, (3) creating synthetic perturbations which are difficult to discriminate from original observations and yet reflect the distribution of “real” errors is hard.

Prior art addresses these issues (1) by reducing the scope of the code to function or line-level, effectively reducing the span of code to say 10 lines of code [16] [31] [32] (2) introducing heuristic perturbations rules or pre-defining a set of categories in which “bugs” fall [16] [6], or (3) perturbing a single line of code in simple programs [31] [6]. While this over-simplification is a reasonable first

step, the resulting dataset may be quite far from realistic errors in the wild for which localization is deemed “useful” to a practitioner.

Our work addresses (1) and (2) by doing away with the notion of an “error” and instead shifting the conceptual thinking toward the distributions of “original” and “perturbed” observations. That is, our dataset is assumed to contain errors that are not identified in the ground-truth labels. The task of error localization is relaxed as the task of localization of perturbations. This relaxation allows us to consider file-level observations without the need for a strict definition of an “error”. In the following, we will provide details on the creation of such data-set and in particular address (3).

3.2 Dataset Construction

The underlying methodology of the creation of this dataset is (1) for learning and evaluation of models gather large amounts of file-level observations (i.e., real code), (2) to introduce synthetic perturbations from a strong generative models such that discrimination of “original” and “perturbed” observation is non-trivial, (3) and relax the task of “error localization” to the task of “perturbation localization”. In the following, we describe the construction of such a dataset.

Observations In order to obtain large quantities of observations for the learning and evaluation of localization models, the proposed dataset is a compilation of public, non-personal information from GitHub consisting of permissively licensed Java code in October 2021. In particular, we gathered 8 million repositories between January 2014 and October 2021 annotated with at least 1 star and considered the subset of contained files containing Java code. The files with are filtered average lines length of ≤ 100 characters, a maximum line length of 1,000, and $\geq 90\%$ of the characters being decimal or hexadecimal digits are removed. Finally, exact duplicates based on their SHA-256 hash are removed, which amounts to a substantial portion of the raw data due to forks and copies of repositories. The resulting data-set comprises 96.56 GB of raw text.

Perturbations For realistic perturbations, we resort to a method known as “inpainting” for images or “infilling” for the textual domain. That is, a portion of a given observation is occluded (or masked out). Then, the occlusion is reconstructed or “filled in” by a sample drawn from a generative model conditional on the non-occluded context. Recently, auto-regressive causal language models [2] have demonstrated to excel at this task for which the prompt may be treated as context and the auto-regressive sample conditional on the prompt as the in-painting while preserving the statistical regularities of the training data. However, the joint distribution over tokens is usually factorized in a left-to-right order over time, for which the causal mask constraints the infill samples to only take past context into account, but not future tokens. In our case of sampling realistic perturbations at random spans within a given observation, we wish to take both the code before and after the masked out span to be taken account, so that file-level consistency remains. To address this issue, we recruit an auto-regressive sampler that re-arranges the input sequence and associated causal masking such that sampling is conditional on both past and future context [7, 11]. To further reduce the gap between “real” and “perturbed” sequences, we chose a large-scale language model, InCoder [11] with 1 billion parameters, and lower the temperature of auto-regressive nucleus sampling to 0.8. Equipped with such a sampler, a random span in the observation is removed and infilled with a sample drawn from the InCoder model. The length of the span is drawn from a uniform distribution with a minimum length of 8 tokens and a maximum length of 64 tokens. The generated sample is constrained to at most the length of the span.

Task Our proposed “perturbation localization” task can be expressed in the form of a binary classification for which each line is labeled as either “original” or “perturbed”. As such, the ground-truth labels indicate whether the line is a sub-sequence of the observation or was (potentially partially) perturbed by the sampler. Each file contains at most one such perturbation. The length of the input sequence is limited to at most 8,192 tokens under the RoBERTa tokenizer [22] with at most 512 lines per file.

3.3 Dataset Examples

To address the aforementioned challenge of creating synthetic perturbations which are difficult to discriminate from the original distribution and yet reflect the distribution of “real” errors, we re-

cruited the large-scale InCoder [11] as an auto-regressive sampler with adjusted causal masking to conditionally sample on a context including future tokens. As a qualitative example, Figure 1 illustrates an original observation on the left-hand side and the perturbed sequence on the right-hand side.

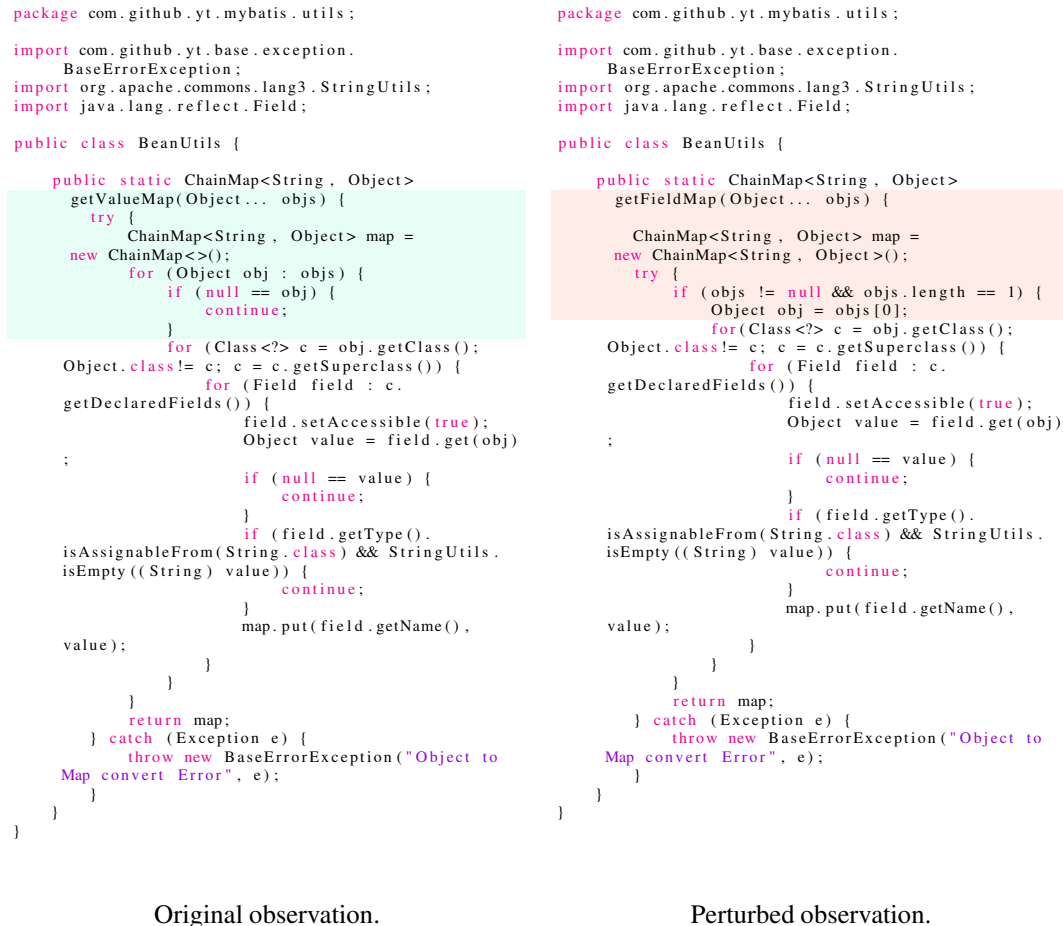


Figure 1: Sampled perturbation introduces a non-trivial rewrite, which may be considered as a “bug”. *Left*: Original Java code iterates over a given list of objects (green highlight). *Right*: Perturbed Java code only considers the first object in the list, if the list contains precisely one element (red highlight).

Remarkably, both sequences appear to be syntactically correct code. The auto-regressive sampler took future tokens into account. For example, the type resolution of the object map may be resolved by the return signature of the function `public static ChainMap<...>` which was not masked out and the invocation of `map.put(...)`. While the original code iterates over the list of objects `obj`, the perturbed code only considers the first element of the list, if the list contains a single element. Whether the rewrites constitute a “bug” depends on the definition of the term, as earlier discussed. However, given the context, one can argue that the rewritten implementation seems less probable to follow the underlying intent.

3.4 Artifacts

The created data-set contains three partitions, training, validation, and evaluation. The training data contains 96.22 GB of raw text, which may suffice to train large language models under recent scaling laws [12]. Details about hosting and accessibility can be found in Appendix A.

4 BigIssue Realistic Benchmark

4.1 Motivation

Based on our observations about existing benchmarks from Section 2, we concluded that a new benchmark was needed to push the state of the art forward. Therefore, we created a benchmark that prioritized quantity over perceived quality and one that focused specifically on NL-based line-level bug localization.

For this benchmark, we defined a line as "buggy" if it has been removed or modified in the issue patch. This allows us to avoid using tests as the ground truth for bugs in code. This definition also fits well with the usage of code encoders such as CodeBERT [9] for line-level classification, as demonstrated in Section 5.

4.2 Benchmark Construction

First, we considered Java GitHub repositories created between January 2014 and October 2021. To ensure that we only filter out repositories that were intended for some form of public use, we only examined repositories with at least 1 star. We further filtered down the repositories to only those repositories that had GitHub Issues enabled and had licenses permitting use of their code. That gave us 4233 repositories.

Using the GitHub API we filtered through closed issues on these repositories. We only used public, non-personal information available through the API. In order to select issues that corresponded to bug fixes on that particular repository, we selected issues that either contained "bug", "fix", or "fixed" as separate words in the title and the body of the issue. We also included issues that contained the label "bug". We looked at issues with a corresponding "close" event, and we looked at the commit that was attached to the latest "close" event. This gave us a dataset of 23,924 total closed issues.

We further subdivide the dataset into single-file and multi-file bugs. Single-file bugs are those that have exactly one modified Java file that doesn't contain any test code. We set these aside as we think these bugs will be easier to locate. We therefore get a set of 10905 single-file bugs and 13019 multi-file bugs.

To mark buggy lines we examine the data from the hunks in the diff. If a line is (1) removed from the source file and (2) is not an import line, it is marked as buggy. In cases where hunks are exclusively adding code, we mark the two lines in the source before and after the change as buggy.

Test-running frameworks Many of the benchmarks presented above use tests either as assistance in bug fixing or as a method of filtering bugs. We do not consider testing frameworks and tests as criteria for whether a commit is a bug or not. Firstly, it was recently shown that unit tests on their own do not guarantee fewer failures inside the code [3] which implies that there are even more bugs inside the code that are not exposed by tests. Secondly, we would be severely limiting the diversity and scope of our benchmark by forcing issues to include an exposing test case.

4.3 Benchmark Examples

In order to show the necessity for long-context models in bug localization, we demonstrate an example of a bug that is highly dependent on external context outside of the scope of the file where the bug is located. The issue ² in question is related to a bug in a minecraft plugin. The bug is that the code calls the global logger instead of the local logger provided via a project-specific class `Varo` and an external library `Bukkit`³. The sample hunk from the diff is presented in 2.

For a human to understand and debug this issue, the human developer needs to know that the class `Varo` exists and is an instance of the `Bukkit JavaPlugin` class. The human reader must also know that the `JavaPlugin` class contains a method called `getLogger` which presents the user with the logger one needs to write to to write to the specific world the plugin instance is active in. For a model to have a chance at finding this bug, it must have access to that context. Without the context, even a human observer cannot reliably mark this as buggy code.

²<http://github.com/AlexanderRitter02/Varo-Plugin/issues/25>

³<https://github.com/Bukkit/Bukkit>

```

int endsze = plugin.getConfig().getInt("border.end-radius")*2;
double shrinkAmountPerHour = plugin.getSettings().getBorderShrinkPerHour();

System.out.println("Worldborder diameter will be shrunken by " + (double) shrinkAmountPerHour + " blocks
every " + timeinterval + " seconds (" + (double) timeinterval / 3600 + " hours).");
plugin.getLogger().info("Worldborder diameter will be shrunken by " + (double) shrinkAmountPerHour + "
blocks every " + timeinterval + " seconds (" + (double) timeinterval / 3600 + " hours).");

String bordermsg = "";
for(World world : Bukkit.getWorlds()) {
    WorldBorder border = world.getWorldBorder();

```

Figure 2: Hunk from sample issue from Varo. This bug demonstrates the need for more context than file-level information.

4.4 Benchmark Artifacts

For each issue, we provide the unfixed and fixed versions, packaged in the `.tar.gz` format. We provide the diff information for that commit, as well as information about the issue from the GitHub API for convenience. Code for processing and obtaining line-level labels for bugs is contained in the code repository. Details about hosting and accessibility can be found in Appendix A.

5 Synthetic vs Realistic Bug Detection

In this Section, we will conduct a preliminary analysis of the hardness of the BigIssues benchmark. Since the sequence length exceeds the limitations of most pre-trained language models on code, we recruit mean pooling to construct a simple baselines. We hypothesize (1) the distribution of perturbed observations generated by even strong generative models still does not resemble real data, (2) localization on real data is significantly harder, (3) long context is required for accurate bug localization. Therefore, future research may put increased emphasis on real data. The findings of our evaluation with the proposed baseline model confirm this hypothesis.

5.1 Hypothesis

The proposed BigIssue benchmark contains two variants: (1) synthetic rewrites of real code sampled from the a strong generative model, (2) realistic rewrites of real code based on the commits associated with a closed issue in GitHub.

Recall, for (1) a recent large language model was recruited as sampler which, compared to prior art, not only is of significant size under scaling laws, but furthermore alters the causal masking such that future tokens can be taken into account as context. We argue that these synthetic rewrites are non-trivial to detect compared to prior art.

However, our hypothesis is that localization of real bugs is still a significantly harder task, which requires substantial research to be solved. While local, trivial bugs do not require context to be localized, harder non-local bugs can often only be resolved when taking the entire file, a set of imported files, or the entire repository into account.

Therefore, one would expect reasonable classification performance of discriminative models on the synthetic rewrites, while the real data poses a much harder task.

5.2 Model

To test this hypothesis, we construct a simple baseline classifier. The model should (1) perform binary classification on a line-level granularity, (2) handle variable length sequences of up to 8,192 tokens and 512 lines, (3) contain a reasonable amount of parameters to have sufficient capacity for solving the task.

Our architecture partitions a long input sequence into shorter sub-sequences, computes contextualized vectors for each chunk using a bi-directional encoder model, combines the contextualized vectors into 512 latent vectors with mean-pooling, and finally projects those vectors to logits for line-level binary classification.

Model	Recall [†]			Precision [†]			F1 [†]		
	Short	Long	Realistic	Short	Long	Realistic	Short	Long	Realistic
Random	49.58	50.51	50.99	2.68	4.71	0.96	5.08	5.99	1.88
Pooling	91.86	91.49	61.99	17.79	7.19	2.32	27.74	13.33	6.35
Pooling-Attn	97.50	97.95	52.88	27.62	21.88	2.41	43.57	35.55	4.61

Table 2: Short and Long refer to short and long synthetic datasets. Comparison of the binary classification accuracy under various baselines: (1) Random Bernoulli classifier with $p = 0.5$, (2) Mean pooling model, (3) Mean pooling model with self-attention between latent vectors.

Consider a sequence $x = (x_0, x_1, \dots, x_n)$ of input tokens with length $n = 8,192$. To address the issue (2) of large n , we partition x into $m = 16$ equally sized chunks \tilde{x}_i with $i \in \{0, \dots, 15\}$ each containing 512 tokens. To contextualize the embedding vector of the tokens, we recruit the pre-trained bi-directional encoder f , CodeBERT [10], and compute $f(\tilde{x}_i)$ for each partition i . Then, the contextualized partitions are concatenated $\hat{x} = (f(\tilde{x}_0), f(\tilde{x}_1), \dots, f(\tilde{x}_m))$. To restore global position information, we apply additive sinusoidal positional embeddings to \hat{x} . Mean-pooling is applied to \hat{x} with a window length such that the resulting sequence of latent vectors matches the maximum number of 512 lines. A layer of self-attention integrates the information across partitions boundaries. A standard linear projection maps each of the line-level latent vectors to logits for binary classification. The resulting model is fine-tuned with binary cross entropy as objective function.

The appeal of the proposed model is to leverage the representations learned by a strong backbone model and the simplicity in handling variable length including line breaks in the input sequence. CodeBERT [10] has demonstrated strong empirical performance on down-stream tasks so that the learned representations should be well suited for bug localization. For simplicity, the mapping of contextualized vectors to latent vectors allows for variable length input sequences and avoids special treatment of new line characters. The alignment from lines of the input sequence to latent vectors for classification is implicitly learned by supervision.

5.3 Findings

To evaluate the hardness of the artificial and realistic BigIssue benchmark, the aforementioned model is trained on both datasets. For synthetic perturbations, the model is trained on 96.22 GB raw code with associated line-level binary labels. We train each model (besides Bernoulli baseline) on a single node with 16 A100 GPUs.

Table 2 summarizes the binary classification performance in terms of recall, precision, and F1-score for three baseline models: (1) A random classifier for which the line-level predictions are modeled as a Bernoulli random variable per line with probability $p = 0.5$, (2) the aforementioned mean-pooling based model for which the self-attention layer between latent vectors is omitted, (3) the mean-pooling based model including self-attention between latent vectors.

For the synthetic dataset, the mean-pooling model including self-attention with an F1-score of 35.55 significantly improves over the random Bernoulli baseline with 5.99. Self-attention to integrate information across latent vectors improves the score by nearly 22 points, which may indicate that long context across the partitioning of 512 tokens is crucial. One may assume with further improvements in modeling, the synthetic dataset is solvable, albeit recruiting a strong generative model to generate synthetic perturbations.

As hypothesized, real bug detection is a much harder challenge for which synthetic perturbations may not be a suitable proxy task. It is our hope that this finding spurs research towards the modeling of long contexts to approach the task of real bug detection.

6 Conclusion

We propose a new benchmark to be used in assessing line-level bug localization models. The diversity and size of the dataset aim to provide a measure with realistic difficulty, encouraging larger context BL modeling that doesn't rely on project test suites. We also provide a synthetically gen-

erated benchmark and show that although the perturbations can be sophisticated and borderline realistic, success on synthetically generated datasets does not transfer to realistic benchmarks.

We hope that our contributions inspire and push future research into realistic, long-context, NLP-based bug localization techniques. Advances in this area would bring automatic program repair to a state that would be useful and transformative to the modern software development process.

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A Data Description, Hosting Details, and Data Access

We publish the training, evaluation, and validation sets for the synthetic data. We also publish the realistic benchmark. These items can be accessed in a Google Cloud Storage bucket at <https://console.cloud.google.com/storage/browser/bigissue-research>.

Realistic Pre-training data For the realistic Pooling and Pooling-Attention models, we created a pre-training dataset similar to other projects. We select Java GitHub repositories with 5 stars or more, we clone the main branch of the repository, while only downloading files under 2 megabytes. We then filter the commits that include the words "error", "bug", "fix", "issue", "mistake", "incorrect", "fault", "defect", "flaw", or "type", using standard practice in ManySStubs4J project [17]. Since our models are designed only for single-file bug localization, we take each modified file and apply the labeling procedure described in the paper to generate the examples and labels. We truncate files at 8192 tokens using the CodeBERT paper [9]. In total, we get about 195 GB of data to use for pre-training.

B Training details

We train all of our models on a single pod with 16 A100 GPUs. We optimized the model with a linear schedule AdamW [23] optimizer, with a starting learning rate of $5e-5$, and 10,000 warmup steps. We train over 200,000 (50,000 for short synthetic dataset) steps with a batch size of 2(8). We provide the full training code at <https://github.com/salesforce/BigIssue>.

Model Checkpoints We provide the model checkpoints for the Pooling and Pooling-Attention models trained on realistic data in the GitHub repository <https://github.com/salesforce/BigIssue>.

C Data Collection Ethical Statement

We did not collect any personal information from the GitHub API. We only collect commit information and data inside the commits, without taking into the account the origin or the user profile of the user making the changes.

This figure "github_diff.png" is available in "png" format from:

<http://arxiv.org/ps/2207.10739v1>