Diffusion is a code repair operator and generator

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Abstract

Code diffusion models generate code by iteratively removing noise from the latent representation of a code snippet. During later steps of the diffusion process, when the code snippet has almost converged, differences between discrete representations of these snippets look like last-mile repairs applied to broken or incomplete code. We evaluate the extent to which this resemblance can be exploited to leverage pre-trained code diffusion models for the problem of last-mile repair by considering two applications with significant potential. First, we can leverage the diffusion model for last-mile repair by adding noise to a broken code snippet and resuming the diffusion process. Second, we can leverage the diffusion model to generate arbitrary amount of training data for last-mile repair tasks (that are computationally more efficient) by sampling an intermediate program (input) and the final program (output) from the diffusion process. We perform experiments on 3 domains (Python, Excel and PowerShell) to evaluate applications, as well as analyze properties. [1]

1 Introduction

Diffusion models have emerged as a powerful paradigm in generative modeling, particularly for tasks that involve complex data structures [Ho et al., 2020]. Instead of generating a sample from a distribution in one go (like a GAN or VAE) or auto-regressively (like a GPT) they learn to iteratively reverse diffusion steps that add (typically Gaussian) noise to the data. Initially popularized in the domain of image generation, diffusion models have since been adapted for modalities like video generation [Ho et al., 2022, Xing et al., 2023]—which requires a temporal component—and text or code generation [Li et al., 2022, Singh et al., 2023a]—which requires diffusion over discrete tokens.

One approach of applying diffusion to discrete domains, like text or code, involves embedding the input, performing diffusion in the embedded representation, and projecting the denoised embeddings back to discrete tokens. To train this model end-to-end, the loss incorporates a component over the discrete tokens, meaning that representation from each step of the reverse diffusion process can be converted back to the discrete space [Lin et al., 2023]. During initial generations, decoding the latent representation does not resemble anything and tokens frequently change, but in later generations, these decoded representations become readable and it takes multiple steps to change one token.

As an example, consider the following generations from pre-trained CodeFusion [Singh et al., 2023a] models—without natural language conditioning—trained on Excel

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[1]The code and associated datasets can be found at `redacted`

ⓐ
Images

$\mathbf{x}_0$ $\mathbf{x}_T$

ⓑ
Code

```
=SUMIFS(
  Orders[TotalAmount],
  Orders[Region],
  "East")
```

```
=SUMIFS(
  [TotalAmount],
  Orders[Region],
  "East"))
```

```
=SUM{Orders[
  TotalAmnt],
  Orders.Region{"},
  'East' ))
```

```
$SDFI*&m@9#!
{Ord$[Tot^Alm_t],
OrD#@[R#eg&on],
'G^ea$T%2!'}
```

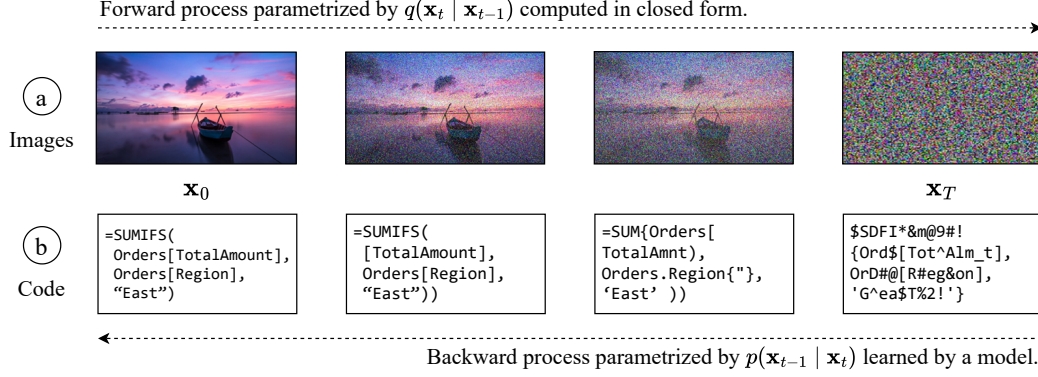Backward process parametrized by $p(\mathbf{x}_{t-1} \mid \mathbf{x}_t)$ learned by a model.

Figure 1: Example of diffusion for ⓐ images and ⓑ code. Pure $\mathbf{x}_T$ is iteratively denoised into a sample $\mathbf{x}_0$ from the target distribution by a model trained on data from the forward process.

$(t_{75\%})$ `=IF(COUNTIF(A:A, '>10')=0, 'No values', AVERAGE(A:A))`
$(t_{90\%} - t_{100\%})$ `=IF(COUNTIF(A:A, '>10')=0, 'No values', AVERAGEIF(A:A, '>10'))`

and Python

$(t_{75\%} - t_{90\%})$ `words = read('myfile').split()`
$(t_{100\%})$ `words = open('myfile').read().split()`

with changed tokens highlighted in red. It appears as if the diffusion model can look at the whole (discrete) program, determine what is missing to make it functional, and apply those fixes. This is exactly the premise of last-mile repair, in which the goal is to repair broken code in such a way that the solution differs minimally from the broken code [Bavishi et al., 2022]. A major challenge in training (last-mile) repair systems is the long-tail problem in obtaining training data [Huang et al., 2023] and out-of-distribution generalization when introducing synthetic errors [Joshi et al., 2024].

In this paper, we address those challenges by evaluating the extent to which discrete token changes during reverse diffusion steps are representative of last-mile repair fixes. This evaluation is broken down in two main applications: whether we can use the diffusion model to **directly repair code**, and whether we can use the diffusion model to **generate training data** for fine-tuning repair models.

We support our claims with experiments on three programming languages: Python, PowerShell and Excel. We find that diffusion models are capable of last-mile repair, with the models being able to repair 56.4–68.2% of Python and Excel snippets across different noise levels. We also find that the diffusion-generated synthetic data has higher diversity and complexity compared to existing data generators and GPT-4o, which is reflected in higher performance observed (+2.5 − 3.5%) when fine-tuning different models (`codet5-small`, `phi-35-mini` and `mistral-7b`) on the synthetic data.

2 Background

2.1 Diffusion models

A diffusion model is a latent variable model that constructs a Markov chain $\mathbf{x}_0, \mathbf{x}_1 \cdots \mathbf{x}_T$ and simulates data $\mathbf{x}_0 \sim p_{\text{data}}$ by learning to reverse this Markov chain [Ho et al., 2020]. The sequence of continuous latent variables $\mathbf{x}_{1:T}$ is constructed by incrementally adding (typically Gaussian) noise to data $\mathbf{x}_0$ until, at diffusion step T, samples $\mathbf{x}_T$ are approximately Gaussian. Each transition $\mathbf{x}_{t-1} \to \mathbf{x}_t$ is parametrized by $q(\mathbf{x}_t \mid \mathbf{x}_{t-1}) = \mathcal{N}(\mathbf{x}_t; \sqrt{1 - \beta_t}\mathbf{x}_{t-1}, \beta_t \mathbf{I})$ where the hyper-parameter β_t is the amount of noise added at diffusion step t. The diffusion model generates samples by reversing this chain: it iteratively denoises the sequence of latent variables $\mathbf{x}_{T:0}$ to approximate a sample from the target distribution. Each denoising transition $\mathbf{x}_t \to \mathbf{x}_{t-1}$ is parametrized by the model that predicts $p_\theta(\mathbf{x}_{t-1} \mid \mathbf{x}_t) = \mathcal{N}(\mathbf{x}_{t-1}; \mu_\theta(\mathbf{x}_t, t), \Sigma_\theta(\mathbf{x}_t, t))$. In practice, instead of constructing the whole chain, we can immediately obtain $\mathbf{x}_t$ from $\mathbf{x}_0$ as $\mathbf{x}_t = \sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t}\epsilon$ with $\bar{\alpha}_t = \prod_{i=1}^t 1 - \beta_t$ and $\epsilon \sim \mathcal{N}(0, \mathbf{I})$. The model $f_\theta(\mathbf{x}_t, t)$ is parametrized to predict $\mathbf{x}_0$ with an empirically validated loss

function $\mathcal{L}_{\text{simple}} = \mathbb{E}_{\mathbf{x}_0,\epsilon_t,t} \| f_\theta(\mathbf{x}_t, t) - \mathbf{x}_0 \|^2$ [Ho et al., 2020, Li et al., 2022]. At inference time, we compute $\mathbf{x}_{t-1} = \sqrt{\bar{\alpha}_t} f_\theta(\mathbf{x}_t, t) + \sqrt{1 - \bar{\alpha}_t}\epsilon$ to iteratively denoise $\mathbf{x}_t$.

Example 1 *Figure 1 shows the generations of a latent diffusion model. It can be seen how the model iteratively denoises to the concrete representation from the output space.*

2.2 Diffusion models for code

Code generation is a discrete generation task, where the expected output is a snippet $\mathbf{c} = [c_1, \ldots, c_k]$ of k tokens. CodeFusion [Singh et al., 2023a] draws inspiration from text diffusion [Li et al., 2022] where each token c_i is embedded $\text{E}(c_i) \in \mathbb{R}^d$ to convert $\mathbf{c}$ into a continuous representation $\text{E}(\mathbf{c}) \in \mathbb{R}^{kd}$ to which a regular diffusion process can be applied. In the reverse process, a trainable rounding step $p_\theta(c_i \mid x_{\leq i})$ computes a distribution over possible tokens for each position i given all previous (denoise) tokens $x_{<i}$. Note that the decoder is trained to always generate a constant number of $n > k$ tokens, one of which is an end-of-sequence token and $n - k - 1$ padding tokens. Like CodeFusion, we set $n = 128$.

Example 2 *Figure 1 shows the generations of a latent code diffusion model. The intermediate representations, when visualized in the discrete token space, show how the model iteratively denoises to a syntactically valid Excel formula. Furthermore, we can see how the generation at $t_{75\%}$ has the table name missing in the structured reference which the model fixes through refinement.*

```
           (t_75%)    =SUMIFS([TotalAmount], Orders[Region], "East"))
(t_90% - t_100%)      =SUMIFS(Orders[TotalAmount], Orders[Region], "East"))
```

More generally, Figure 2 shows trends in discrete code refinement over subsequent diffusion time-steps as (a) the number of tokens being changed and (b) the lengths of spans of tokens that are changed at once. As expected, significantly fewer tokens are changed further down the diffusion process. These trends of fewer and localized edits near the end of the diffusion process motivate the application of the diffusion process for last-mile repair.
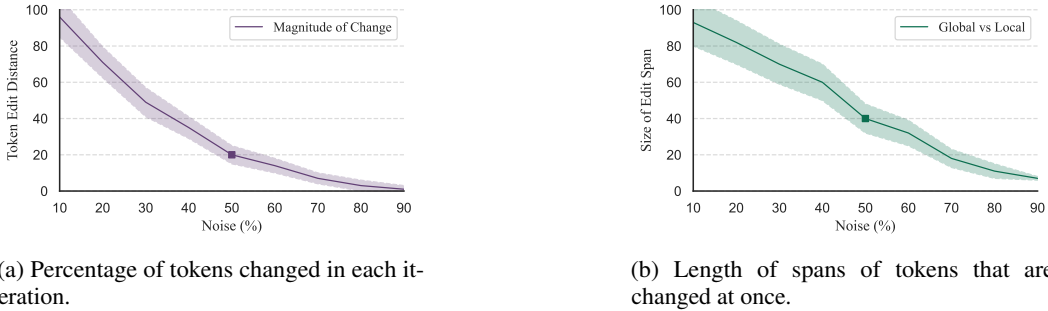

(a) Percentage of tokens changed in each iteration.

(b) Length of spans of tokens that are changed at once.

Figure 2: Trends in code refinement over diffusion time steps.

3 Diffusion for repair

Let $\hat{c}$ be a buggy code snippet that is not accepted by the compiler. The goal of last-mile repair is to find a code snippet $c^* = \arg\min_c d(c, \hat{c})$ such that c^* is accepted by the compiler and performs a task intended by the user, with d the edit distance between two code snippets. Like previous work on last-mile repair, we only consider syntactic errors [Bavishi et al., 2022, Joshi et al., 2023]. In the following three sections, we respectively reiterate the components and training process of CODEFUSION, describe how to apply it to problem of last-mile repair, and describe how to generate pairs $(\hat{c}, c^*)$ that can be used to train specialized systems.

3.1 Training the diffusion model

The pre-trained components of CODEFUSION generate code from pure Gaussian noise. Because there is no natural language, we can remove the encoder. A denoiser N removes the noise from
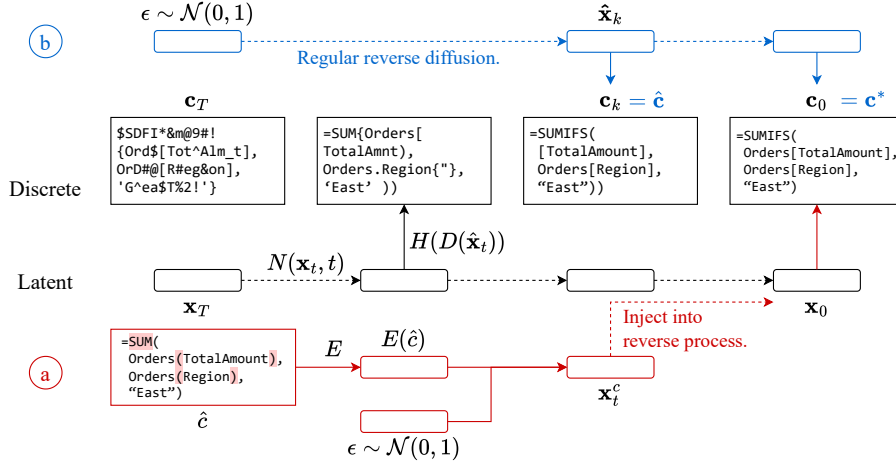
Figure 3: Using a pre-trained diffusion process (in black) to (a) repair broken code and (b) generate (broken, fixed) code pairs for training specialized approaches. (a) The broken code is embedded, noise is added for a timestep t, and the reverse process is resumed as usual, letting the reverse process fix the code. (b) The diffusion process produces intermediate (broken) code snippets $\hat{c}$ that can be paired with the final code c^* to form a training example.

x_t at timestep t to obtain the denoised embeddings $\hat{x}_0 = N(\mathbf{x}_t, t)$. A decoder D performs full self-attention over $\hat{x}_0$ to compute a decoded representation $D(\hat{x}_0)$. This allows each denoised token to be generated with information about other tokens, and improved the likelihood of generating syntactically correct code [Singh et al., 2023a]. Finally, the classification head H computes $p(y \mid d_i)$ for each $d_i \in D(\hat{x}_0)$ to project decoded embeddings back to discrete tokens.

To train these components on a code snippet $\mathbf{c}$, an embedding layer E first obtains the continuous representation $\mathbf{x}_0 = E(\mathbf{c})$. We sample $t \in [1, \dots, T]$ and $\epsilon_t \sim \mathcal{N}(0, 1)$ and compute $\mathbf{x}_t$ from $\mathbf{x}_0$. The model is trained on

$$\mathcal{L} = \underbrace{\|N(\mathbf{x}_t, t) - \mathbf{x}_0\|}_{1} + \underbrace{\|D(\hat{x}_0) - E(\mathbf{c})\|}_{2} - \underbrace{\text{ce}(\mathbf{c}, H(D(\hat{x}_0)))}_{3}$$

and consists of three parts that

1. minimize the error between the predicted noise $\hat{\epsilon}_t$ and the actual noise ϵ_t to train N,

2. minimize the error between the decoded embeddings $D(\hat{x}_0)$ and embedded code $E(\mathbf{c})$ to train D and L, and

3. apply cross-entropy loss with respect to the ground truth code snippet $\mathbf{c}$ to train H.

This loss is taken from CODEFUSION [Singh et al., 2023a] and is an adaptation of the loss function used by GENIE [Lin et al., 2023].

3.2 Diffusion steps as repair *operators*

We exploit the Markov property of the reverse diffusion process to *inject* an embedded version of the noisy snippet into the reverse process. In other words, we can pick some t, generate $\epsilon \sim \mathcal{N}(0, 1)$ and compute $\mathbf{x}_t^{\hat{c}} = \sqrt{\bar{\alpha}}E(\hat{\mathbf{c}}) + \sqrt{1 - \bar{\alpha}_t}\epsilon$ where E is the embedding layer (that CodeFusion discards after training). The diffusion process then denoises $\mathbf{x}_t^{\hat{c}} \to \mathbf{x}_0^{\hat{c}}$ and we return $H(D(N(\mathbf{x}_0^{\hat{c}}, 0)))$.

Let $\mathbf{X}_t^{\hat{c}}[E]$ be the space of embedded representations $\mathbf{x}_t^{\hat{c}}$ obtained from $\hat{\mathbf{c}}$ for all $\epsilon \sim \mathcal{N}(0, 1)$ at step t (parametrized by E). Let $\mathbf{X}_t^{c^*}[N, D, H]$ be the space of embedded representations encountered at step t in reverse diffusion processes starting from $\epsilon \sim \mathcal{N}(0, 1)$ that end up in $\mathbf{c}^*$ (parametrized by N, D and H). Our intuition is that there exists some t for which these spaces have a significant

overlap, and there are thus many values of ϵ that project $\hat{\mathbf{c}}$ into a trajectory to $\mathbf{c}^*$. If t is too large, the probability of ending up there is small (too much noise). If t is too small, it will never end up there (not enough noise).

3.3 Diffusion models as repair *generators*

We exploit the seemingly discrete nature of later diffusion steps to generate synthetic repair data. Starting the reverse process from $\mathbf{x}_T \sim \mathcal{N}(0, 1)$ we build the chain $\hat{\mathbf{x}}_T \to \hat{\mathbf{x}}_0$ and decode each snippet into $\mathbf{c}_T \to \mathbf{c}_0$. We can then select any $(\mathbf{c}_t, \mathbf{c}_0)$ as a training pair if $\mathbf{c}_t \neq \mathbf{c}_0$.

In previous work, mistakes are introduced in the discrete token space, by implementing specialized functions that imitate human errors [Yasunaga and Liang, 2020, Joshi et al., 2024, Singh et al., 2025, Singha et al., 2024] and optionally training a neural network to imitate those [Yasunaga and Liang, 2021]. We show that the space of discrete representations encountered during the reverse diffusion process shares enough similarities to the discrete last-mile repair errors.

4 Experiments

We evaluate both how the diffusion process acts as a repair operator, how the generated data can be used for supervised repair training, providing insights on how diffusion generates (and repairs) code.

4.1 Experimental Setup

Benchmarks   We evaluate our approach on three different benchmarks that span different types of code (formulas, code, commands).

1. **Excel** [Bavishi et al., 2022] is a benchmark of 200 broken formulas collected from a public Excel help forum[2].

2. **PowerShell** [Joshi et al., 2023] is a repair benchmark for 208 PowerShell commands collected from StackExchange[3] by comparing commends in the question with those in accepted answers.

3. **Python** [Yasunaga and Liang, 2021] is a code repair benchmark collected from GitHub. We evaluate on a random sample of 200 syntactically invalid Python code snippets. These do not have a ground truth repair, hence, we employ the same evaluation metric described in the BIFI paper using (1) syntactic validity and (2) token edit distance < 5.

Pre-training data   Collecting snippets of code for unsupervised approaches is significantly easier than finding data for repair.

1. For **Python**, we use a collection of 130K code snippets for simple tasks with an average token length of 79.4 tokens from existing benchmarks [Yasunaga and Liang, 2021].

2. For **Excel**, we use a corpus of 1.8 million workbooks [Singh et al., 2022a, Payan et al., 2023], and sample 200K workbooks and collect all formulas present in them to generate 108K unique formulas with an average length of 35.8 tokens.

3. For **PowerShell**, we collect PowerShell commands from public websites. The corpus has 110K samples with an average length of 24.9 characters.

Metrics   When available, we use execution match—comparing the output of executing the repaired code with an expected output—which allows for semantically different but functionally equivalent code snippets. To further analyze the syntactic closeness of the repairs to the original code, we also report sketch match, which is implemented as the exact string match of code with constants (strings, numbers, cell references) anonymized.

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[2]`www.mrexcel.com`
[3]`www.stackexchange.com`

Table 1: Repair results for CodeFusion. We report sketch and execution match for all languages at different noise pooling settings.

Noise pooling	Python		PowerShell		Excel	
	Sketch	Execute	Sketch	Execute	Sketch	Execute
any%	65.3	68.1	14.3	21.2	62.3	63.4
best%	60.4	62.0	11.0	17.4	56.2	58.9
vote%	61.2	62.4	11.7	18.2	57.1	59.1

Models We implement the same architecture and pre-training as CodeFusion [Singh et al., 2023a]. The **embedding** (E) has a dimension of 512. The **denoiser** (D) is a transformer encoder [Vaswani et al., 2017] with 10 transformer blocks. The **decoder** (D) is a block with 6 transformer decoder layers. The **classification head** (H) is a single fully connected layer.

Compute All training was done on a 8 x A100 cluster (Azure `NDm_A100_v4`).

4.2 Diffusion for code repair

We evaluate a pre-trained diffusion model on last-mile repair. Table 1 contains the execution and sketch match, pooled across noise levels using three strategies, for different diffusion architectures. In **any%**, any noise level was able to correctly repair the code for each sample, indicating the promise of diffusion for repair. In **best%**, we pick the best global noise level for each benchmark set, which are indicated in Figure 4. In **vote%**, we pick the repaired code that was obtained most often across noise levels (using exact string match). Our findings show that vote-pooling across noise levels is *slightly* more effective than the *free lunch* of an optimal noise level.

Figure 4 shows how the execution match evolves in function of the noise level (increments of 10%) and marks the "optimal" noise level (based on average + one standard deviation). Last-mile repairs are typically small, causing all lower noise levels to work. For larger noise levels, we see a decline in performance, as the model makes too many changes to the code.

Additionally, we examine how error complexity correlates with the noise levels required for repair. Figure 5 shows an area plot of maximum and minimum noise levels where the correct code is generated at least once with increasing complexity, computed as normalized edit distance for the repair tasks. The results suggest the acceptable noise band varies based on the complexity where an earlier injection is preferred for more complex tasks as these require more iterations to repair. Furthermore, across languages, we see that Excel has a much wider band as it requires fewer edits while for Python and PowerShell more edits are required for the repair.
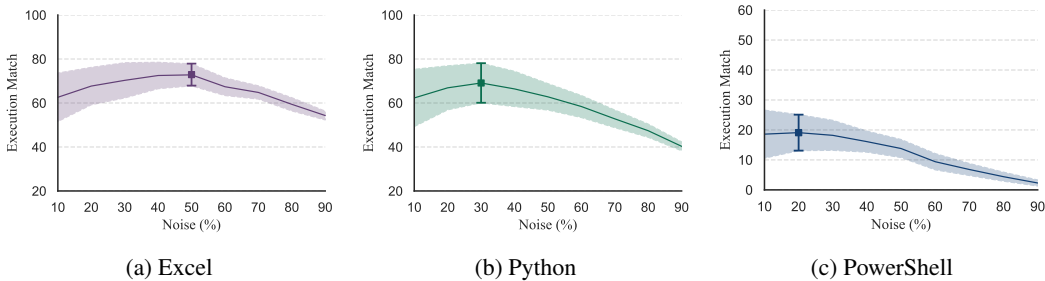

(a) Excel	(b) Python	(c) PowerShell

Figure 4: The evolution of execution match for increasing noise levels added to the noisy snippet ($\hat{c}$). The optimal noise level is marked. We find that for simpler languages like formulas, injecting later helps while for more complex languages like Python and PowerShell, injecting earlier gives the model more time to repair to the correct code.

To put our results in perspective, Table 2 compares the pass@1 rate of the pre-trained diffusion model with existing approaches. For LaMirage [Bavishi et al., 2022] and BIFI [Yasunaga and Liang, 2021] we report the numbers from their respective papers. For the other approaches, we re-implement them,
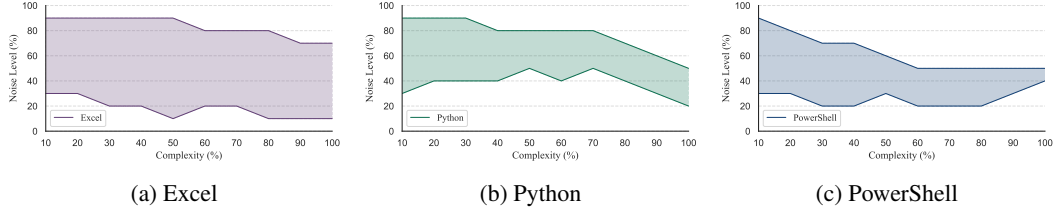
| (a) Excel | (b) Python | (c) PowerShell |

Figure 5: Noise range for which the correct code snippet is recovered for increasing differences between the broken and fixed code. We show the maximum and minimum noise for which a sample was repaired correctly. The band width is largest for Excel since it requires simpler and fewer changes while PowerShell has a narrow band towards higher noise as it needs more iterations to repair.

with the Codex [Chen et al., 2021] and GPT-4o results based on the RING prompt without compiler feedback. We note that these very powerful models (GPT-4o), specific repair systems (BIFI and LaMirage) and using additional context (RING) still perform better. Still, outperforming the Codex model on Python (+8%) and PowerShell (+11%) with a small (60M parameter) model that was not specifically trained for repair, is a remarkable result that indicates significant potential of applying diffusion to code repair.

Table 2: Comparison performance of CodeFusion with state-of-the-art last-mile repair approaches.

			Python		Excel		PowerShell	
Approach	Type	Year	Sketch	Exec.	Sketch	Exec.	Sketch	Exec.
Codex	Prompt	2021	0.56	0.60	0.65	0.67	0.08	0.10
RING	Prompt	2022	0.78	0.82	0.68	0.74	0.15	0.18
GPT-4o	Prompt	2024	0.81	0.84	0.68	0.75	0.15	0.24
GPT-4.1	Prompt	2025	0.82	0.83	0.67	0.76	0.14	0.24
GPT-o1	Prompt	2025	0.81	0.82	0.65	0.74	0.12	0.21
LaMirage	Fine-tuned	2022	0.67	0.71	0.69	0.72	–	–
BIFI	Fine-tuned	2021	0.72	0.76	–	–	–	–
CodeFusion	Pre-trained	–	0.65	0.68	0.62	0.63	0.14	0.21

A major advantage of CodeFusion is its ability to generate diverse outputs, as it is conditioned on noise. Table 3 shows the pass@1, pass@3 and pass@5 rates for diffusion, GPT-4o and RING. CodeFusion sees the biggest jump in performance ($\pm$ 5%) across all languages, even performing better than GPT-4o on the (most difficult) PowerShell benchmark. This reinforces the potential of diffusion for last-mile repair. Pooling over different noise vectors, execution feedback and larger diffusion models can leverage this potential even further, which we leave for future work.

Table 3: Pass@k rates for repair for the best diffusion model adapted for repair (CodeFusion). The performance for CodeFusion increases with k, as it generates diverse repairs due to its noise condition.

	Python			Excel			PowerShell		
Approach	p@1	p@3	p@5	p@1	p@3	p@5	p@1	p@3	p@5
CodeFusion	68.1	70.5	72.4	63.4	65.8	68.2	21.2	23.1	26.4
GPT-4o	81.2	81.7	82.1	75.3	75.6	75.7	23.9	24.1	24.2
GPT-4.1	81.3	81.6	82.2	75.4	75.7	75.7	23.8	24.2	24.3
GPT-o1	81.1	81.4	82.0	75.3	75.4	75.5	23.5	24.0	24.2
RING	82.4	82.6	82.9	73.8	74.2	74.5	18.0	18.0	18.2

4.3 Diffusion for synthetic data generation

We evaluate the pre-trained diffusion model (CodeFusion architecture) on generating training data for supervised approaches. We uniformly sample t and select $(\mathbf{c}_t, \mathbf{c}_0)$ from the diffusion process. We

then fine-tune several code generation models on this dataset and evaluate their performance on a repair benchmark containing real human errors. We sample 20K training points.

As baselines, we consider generators from existing work, as well as generating data with a large language model (GPT-4o). For Python, we use the popular BIFI [Yasunaga and Liang, 2021] model, which learns to break code based on a set of manually curated repair operators. For Excel, we use the 17 operators used to fine-tune `FLAME` [Joshi et al., 2024] on last-mile formula repair. The prompt for GPT-4o is a few-shot, chain-of-thought prompt where we instruct the model to break a formula according to mistakes that a human would make. We use two versions: (1) using error categories from BIFI to mimic human errors and (2) not providing guidance to promote diversity in mistakes.

Table 4 shows the performance of different data generation techniques across various models: CodeT5+ (2B) [Wang et al., 2023], Phi-3.5-mini-instruct (3.8B) [Abdin et al., 2024] and Mistral-7B-instruct-v0.3 (7B) [Jiang et al., 2023]. Our results show that models trained on diffusion-generated consistently outperform with other specialized approaches, across all models. Similar to repair, a significant contributor is the diversity in the generated data, which is harder to control for GPT-4.1.

We analyze properties of the generated data distributions for diffusion and GPT-4o in Figure 4. We show the average distance between token edits (localization), average n-gram similarity between randomly sampled data points (diversity), and average token edit distance between the noisy and correct code (complexity). Diffusion-generated data has more diversity, higher complexity, and more global errors. The diffusion model generates both the code and the error from pure noise, whereas GPT-4o starts from provided code.

Table 4: Results on fine-tuning different language models on the synthetic repair data generated by diffusion, GPT-4.1 and Syntactic systems (BIFI [Yasunaga and Liang, 2021] for Python and `flame` [Joshi et al., 2024] for Excel). We see that diffusion-generated data consistently performs better than language model and syntactic systems.

Generator	Repair model	Python		PowerShell		Excel formula	
		Sketch	Exec.	Sketch	Exec.	Sketch	Exec.
Diffusion	CodeT5+ (2B)	**89.2**	**91.1**	25.4	**34.2**	72.0	**77.6**
	Phi-3.5-mini-instruct (3.8B)	87.5	88.3	**28.2**	33.2	71.0	76.8
	Mistral (7B)	87.1	89.3	27.4	**34.2**	**73.3**	75.6
GPT-4.1	CodeT5+ (2B)	87.6	88.2	23.4	28.1	69.2	72.1
	Phi-3.5-mini (3.8B)	84.2	86.9	21.0	27.3	70.1	74.3
	Mistral (7B)	85.4	87.7	24.5	29.4	69.3	70.0
Syntactic	CodeT5+ (2B)	85.4	87.3	–	–	70.1	72.4
	Phi-3.5-mini (3.8B)	84.2	85.3	–	–	72.4	**77.6**
	Mistral (7B)	86.0	89.3	–	–	71.2	73.5

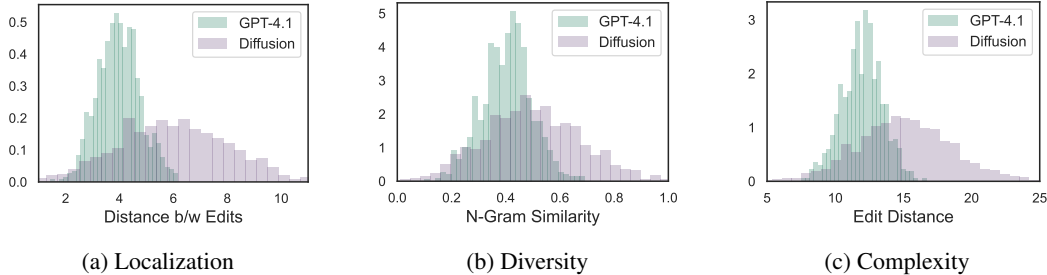(a) Localization   (b) Diversity   (c) Complexity

Figure 6: Figure showing the trends in the diffusion (purple) and GPT-4.1 (green) generated repair data. We show (a) Localization—average distance between edits; (b) Diversity—average n-gram diversity in generated correct code; and (c) Complexity—edit distance of the repair.

Finally, Figure 7 shows the overlap between Excel benchmarks solved using the CodeT5+ model for different sources of synthetic data. Using diffusion data solves all cases that are solved by the synthetic data, which required manual analysis of human errors to manually implement 17 noise
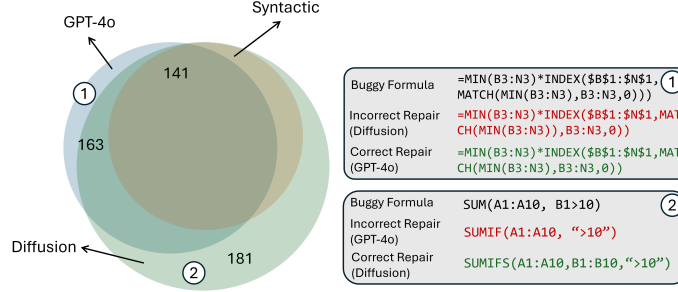
Figure 7: Venn diagram of benchmarks solved correctly for models trained on synthetic datasets generated from different sources. The example shows cases where diffusion data trained model is able to repair a task while GPT-4o data trained model cannot and vice versa.

operators. Bigger mistakes, like completely missing an argument spanning multiple tokens, occur more in the diffusion data. An extra parenthesis does not occur as much in the diffusion data, as the pre-trained models quickly learns this structure, and is an explicit instruction in the GPT-4o prompt.

5 Related work

Diffusion models for text and code Diffusion models have shown their ability to gradually refine noisy data into realistic outputs through a denoising process [Sohl-Dickstein et al., 2015]. They were originally popularized to generate photo-realistic images [Ho et al., 2020, Rombach et al., 2022] and later applied to other high-dimensional data generation, like audio [Kong et al., 2021] and video [Ho et al., 2022] synthesis. Diffusion has also been adapted for to discrete domains like text [Li et al., 2022, Lin et al., 2023] and code [Singh et al., 2023a] where the ability to look at the whole previous generation has benefits over auto-regressive generation. Two approaches are embedding discrete tokens into a continuous space where the diffusion takes place and then decoding Li et al. [2022] or directly performing diffusion in the discrete space through a transition matrix He et al. [2023].

Code repair Automated code repair [Zhang et al., 2023] has long been a key challenge in software engineering, with early approaches using heuristic searches [Qi et al., 2014] and program synthesis [Nguyen et al., 2013, Bavishi et al., 2022]. More recently, transformer-based systems have been shown adept at learning to repair code [Berabi et al., 2021, Yasunaga and Liang, 2021, Tufano et al., 2019, Khatry et al., 2023, Singh et al., 2022b]. A major limitation of training a repair model is the requirement for large quantities of data. That is not true anymore for large language models, which are adept at repair code and can take in additional context like error messages [Joshi et al., 2023]. In order to leverage the corpora of unsupervised data, previous works have explored generating synthetic data using static rules [Joshi et al., 2024, Gupta et al., 2017, Hellendoorn et al., 2019] or learning to break programs in a *natural* way [Yasunaga and Liang, 2020, 2021]. These approaches are limited to the encoded rules and the quality of the learned code breaker, and thus suffer from out-of-domain generalization.

6 Conclusion and limitations

In this paper, we explored the potential of applying pre-trained code diffusion to the problem of last-mile repair. These diffusion models iteratively denoise a latent representation of code and the discrete decoding of intermediate steps resemble last-mile programming errors. Our experiments show that injecting actual broken code into this process can cause the diffusion process to repair the code, and that sampling these intermediate step yields data that can be used to fine-tune last-mile repair models. In its current state, using diffusion models to generate synthetic training data shows the most promise.

Diffusion for code has only been applied to shorter snippets with smaller models, on relatively small datasets. Since there is no additional context, like error messages or test cases, the model might not capture some of the semantics of the broken snippet. Our findings consider the diffusion model as-is:

controlled decoding [Li et al., 2022, Singh et al., 2023b] can help in remaining close to the source snippet.

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