Edit-Based Refinement for Parallel Masked Diffusion Language Models

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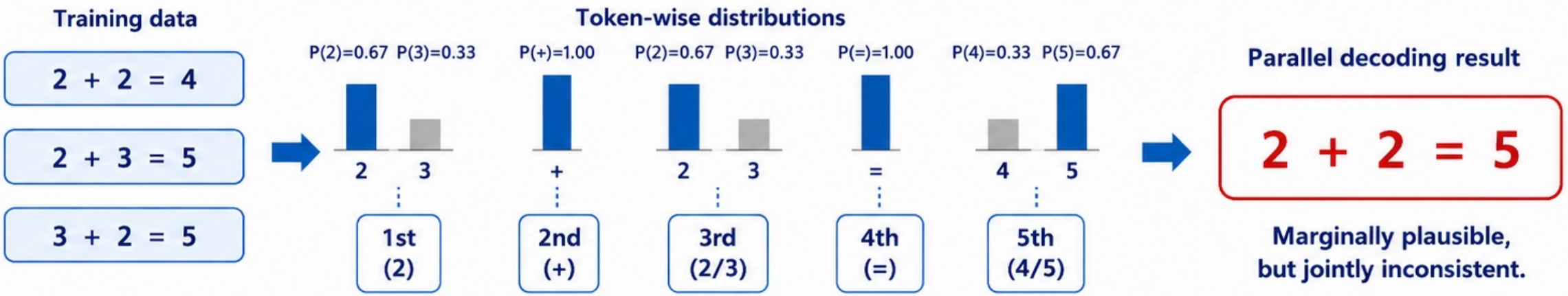
Background

Masked Diffusion Language Models (MDLMs)

- Generate text by progressively unmasking tokens rather than left-to-right decoding
- Enable parallel prediction across positions
- Offer attractive decoding efficiency and scalability

Main Limitation

- Training optimizes token-wise denoising / marginal prediction
- Parallel multi-token decoding predicts several positions simultaneously
- Locally likely tokens may form globally inconsistent sequences



Key challenge:
Bridge the gap between token-level training and sequence-level consistency.

Methods

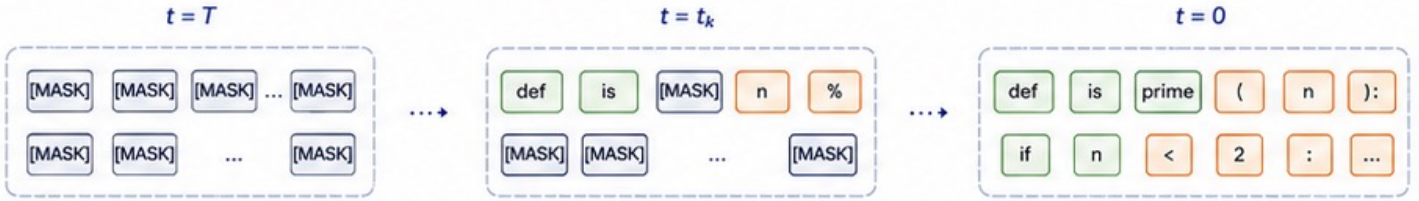
ME-DLM adopts a two-stage framework:
(1) Masked diffusion generates a coarse sequence in parallel; (2) Edit diffusion performs lightweight refinement via minimal edit operations to improve global consistency.

1 Stage 1: Masked Diffusion (Coarse Generation)

Input (Prompt)

Q: Write a function to check whether a number is prime.

Reverse Diffusion Process (T steps)



Coarse Output
(may be inconsistent)

```
def is_prime(n):
    if n < 2:
        return False
    if n % 2 == 0:
        return False
    return True
    ...
```

e.g., missing final loop

- Starting from a fully masked sequence, the model progressively denoises all positions in parallel.
- Fast generation with high efficiency.
- However, the coarse output may contain structural or logical inconsistencies.

2 Stage 2: Edit-Based Diffusion (Refinement)

Coarse Output

```
def is_prime(n):
    if n < 2:
        return False
    if n % 2 == 0:
        return False
    return True
    ...
```

Edit Operations (Token-wise)

For each position i, predict (c_i, n_i)

Replace / Keep	If $c_i \neq [DEL]$, replace x_i with c_i; if $c_i = x_i$, keep unchanged.	x_i = old → c_i = new
Delete	If $c_i = [DEL]$, remove the current token x_i.	x_i = token → $[DEL]$
Insert	Predict n_i after position i; if $n_i \neq c_{i+1}$, insert n_i between c_i and c_{i+1}.	c_i + n_i + c_{i+1}

Edits are predicted in parallel, conditioned on the full sequence.

Refined Output

```
def is_prime(n):
    if n < 2:
        return False
    if n % 2 == 0:
        return False
    for i in range(3, int(n**0.5)+1):
        if n % i == 0:
            return False
    return True
```

- Predict minimal edit operations (replace / delete / insert) to transform the coarse sequence.
- Conditions on the full sequence to model global dependencies.
- Produces a refined sequence with improved consistency and correctness.

Experiments

ME-DLM consistently improves performance, and the gains become larger under more aggressive parallel decoding.

Average Performance Across 4 Benchmarks

Budget	Stage-2	Stage-3	Gain
1/1	55.7	60.0	+4.3
1/2	50.7	55.4	+4.7
1/4	37.7	46.4	+8.7
1/8	19.3	32.6	+13.3

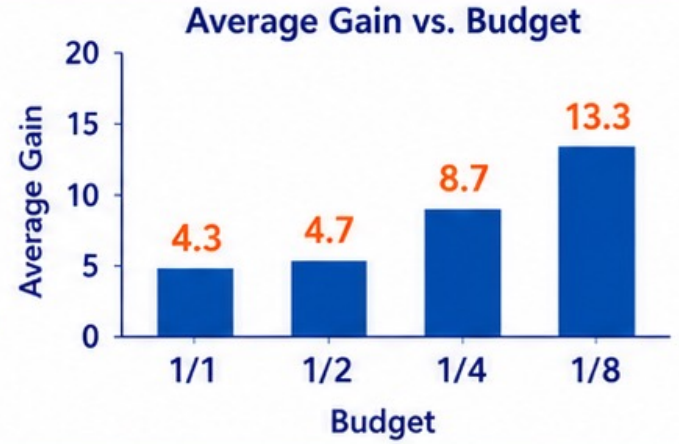
Average over HumanEval, HumanEval+, MBPP, MBPP+, GSM8K, and MATH-500. Lower budget = more aggressive parallel decoding.

Representative Improvements at Budget 1/8

HumanEval	MBPP	GSM8K	MATH-500
+11.6	+4.7	+33.6	+16.6

Key Findings

- Stage-3 outperforms Stage-2 at every budget.
- Gains are strongest in low-step, high-parallelism settings.
- Improvements hold across both code and math tasks.



Takeaway: | Edit-based refinement is most beneficial when parallel decoding is aggressive.

Experiments

Example: code generation under aggressive parallel decoding. A few localized edits turn a flawed draft into a correct program.

Mask Diffusion (Coarse Output)

Prompt: Write a Python function to recursively sum a nested list.

```
def recursive_list_sum(lst):
                                    ← missing total = 0
    for item in lst                 ← missing ':'
        if isinstance(item, list):
            total += recursive_list_sum(item)
        else:
            total += item
    return total
```

Non-executable / structurally inconsistent

Localized Edit Actions

1. **Insert** `total = 0` after the function header.
2. **Replace** `for item in lst` with `for item in lst:`
3. **Preserve** the remaining structure and tokens.

Edits are conditioned on the full sequence and applied with minimal changes.

ME-DLM (Refined Output)

```
def recursive_list_sum(lst):
    total = 0
    for item in lst:
        if isinstance(item, list):
            total += recursive_list_sum(item)
        else:
            total += item
    return total
```

Executable and logically consistent

Takeaway: ME-DLM preserves most tokens and fixes only the critical local errors, restoring global program correctness.

Conclusion

ME-DLM improves sequence-level consistency for parallel MDLMs while preserving the efficiency of parallel diffusion decoding.

Conclusion

1. Parallel MDLMs suffer from a mismatch between token-wise training and joint sequence consistency.
2. ME-DLM addresses this with a two-stage pipeline: coarse mask diffusion plus edit-based refinement.
3. Minimal replace / delete / insert operations, conditioned on the full sequence, correct local inconsistencies.
4. ME-DLM achieves consistent improvements on code and math benchmarks, especially under aggressive parallel decoding.

Future Work

- Explore training-free or lighter-weight mechanisms for enforcing sequence-level constraints.
- Study adaptive edit scheduling and stopping criteria.
- Extend evaluation to broader tasks, longer outputs, and more general instruction-following settings.
- Explore flexible-length refinement and richer edit strategies for more powerful generation.

Thank You!