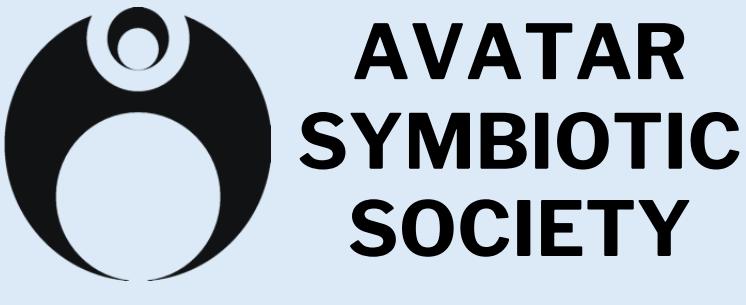


Speech Synthesis with Perceptual Rating-Guided Parallel Iterative Decoding



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Overview

Purpose:

- Explore **inference-time optimization** methods leveraging speech perceptual quality ratings for text-to-speech (TTS)
- Focus on TTS model based on **parallel iterative decoding**

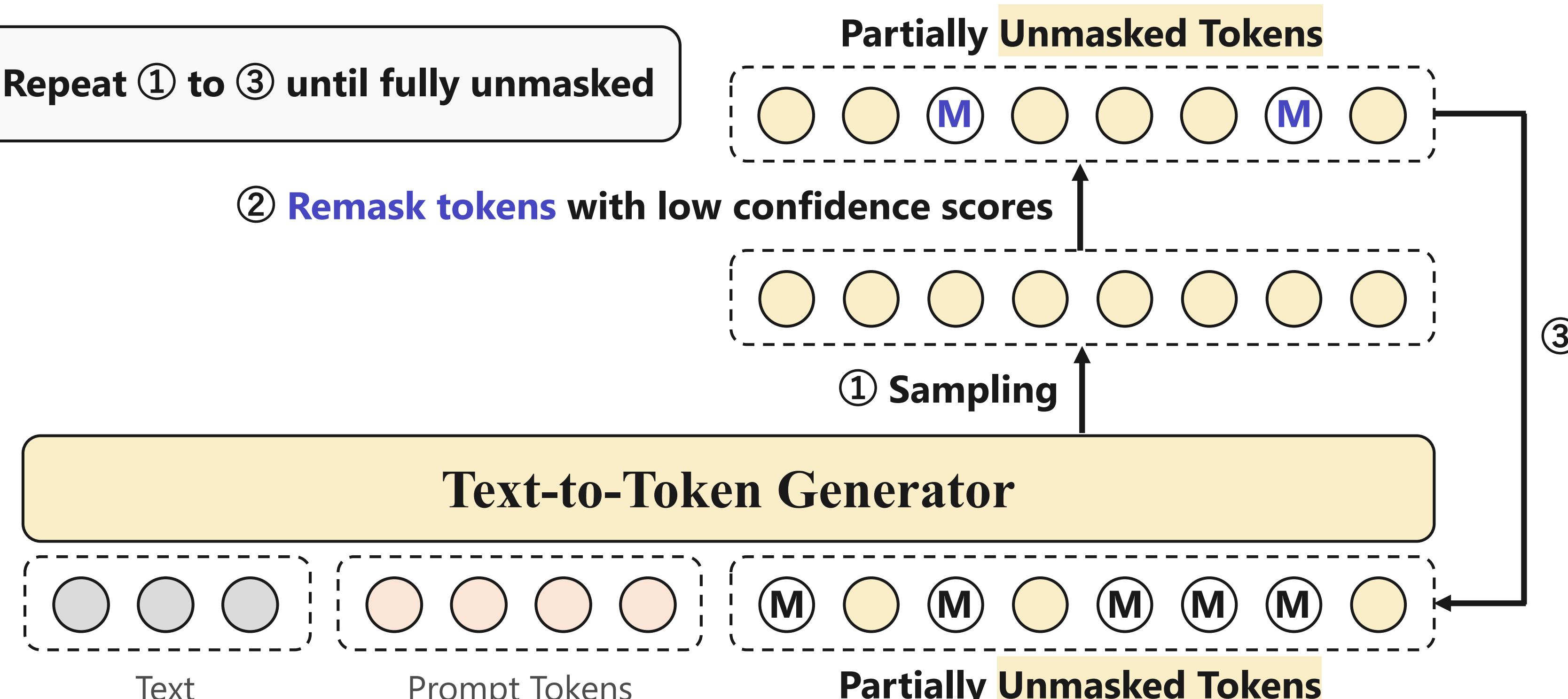
Proposal: Perceptual Rating-Guided Parallel Iterative Decoding

- Introduce naturalness and speaker similarity guidance to parallel iterative decoding
- Improve zero-shot TTS performance

Background

Masked Generative Codec Transformer (MaskGCT) [Y. Wang+24]

- Zero-shot TTS model based on **parallel iterative decoding**
- TTS pipeline: Text & Speech Prompt → Speech Tokens → Waveform



Advantages:

- High prosodic diversity due to gradual sampling of tokens
- High controllability over duration than autoregressive TTS model

Challenges:

- Selecting tokens to unmask based solely on the token's confidence score (= probability) **does not necessarily result in perceptually optimal speech quality**

Exploring **inference-time optimization** methods to optimize perceptual speech quality ratings during inference

Proposed Method

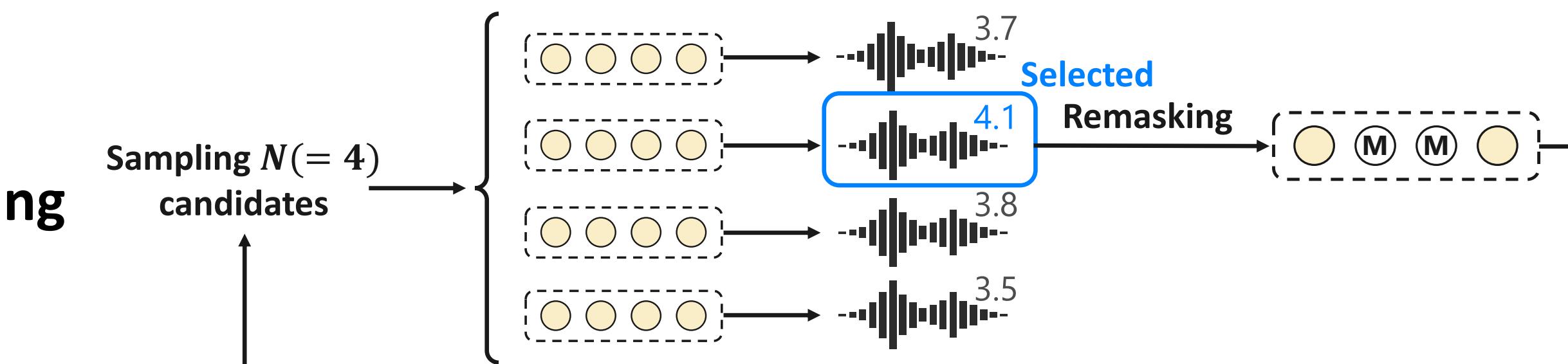
Proposed method: Perceptual Rating Guidance

- Multiple candidate tokens are sampled and evaluated, and the most perceptually promising candidate is selected

Explore three variants:

- Guided Decoding:** Iterative selection at each decoding step
- Best-of-K (BOK):** One-shot selection after the whole decoding
- Hybrid approach: Combining Best-of-K & Guided Decoding**

➤ Generate K speech samples using Guided Decoding → Best-of-K selection



Overview of (1) Guided Decoding

Perceptual ratings:

- Naturalness: Predicted mean opinion score (MOS) by UTMOS [T. Saeki+22]
- Speaker similarity (SpkSim): Cosine similarity between speaker embeddings of prompt and synthesized speech
 - Speaker embeddings are taken from a pre-trained ECAPA-TDNN [B. Desplanques+20]

Experiments

Experimental settings:

- Backbone zero-shot TTS model:
 - Pre-trained MaskGCT [Y. Wang+24]
- Dataset for evaluation:
 - SeedTTS test-en dataset [P. Anastassiou+24]
 - Approximately 500 speakers \times 2 samples from Common Voice Dataset [R. Ardila+19]

Evaluation metrics:

- Naturalness MOS (N-MOS)
 - 1 (very unnatural) to 5 (very natural)
- Speaker similarity MOS (S-MOS)
 - 1 (not at all similar) to 5 (very similar)
 - Similarity between prompt and synthesized speech

Results of subjective evaluation:

- Our method, especially based on UTMOS, significantly **improves naturalness and speaker similarity** compared to the original
- Combining Best-of-K and Guided Decoding **improved the scores**

Method	N-MOS (\uparrow)	S-MOS (\uparrow)
Ground truth	4.00 ± 0.07	3.86 ± 0.09
MaskGCT (Original)	2.63 ± 0.08	2.42 ± 0.08
MaskGCT w/ BOK-UTMOS ($K = 16$)	2.89 ± 0.08	2.51 ± 0.08
MaskGCT w/ BOK-SpkSim ($K = 16$)	2.68 ± 0.08	2.42 ± 0.09
MaskGCT w/ Guide-UTMOS ($N = 16$)	2.82 ± 0.08	2.44 ± 0.09
MaskGCT w/ Guide-SpkSim ($N = 16$)	2.80 ± 0.08	2.43 ± 0.08
MaskGCT w/ BOK & Guide-UTMOS ($K = 4, N = 4$)	2.93 ± 0.08	2.56 ± 0.09
MaskGCT w/ BOK & Guide-SpkSim ($K = 4, N = 4$)	2.79 ± 0.08	2.51 ± 0.09

250 native English speakers each evaluated 24 samples.

*-UTMOS and *-SpkSim denote BOK or Guided Decoding based on UTMOS and SpkSim.

Conclusion & Future Work

Conclusion:

- Combining **Best-of-K** and **Guided Decoding** based on perceptual ratings **improved zero-shot TTS performance**

Future work:

- Extend perceptual ratings to various ratings, such as NISQA [G. Mittag+21], and **multi-objective ratings**

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