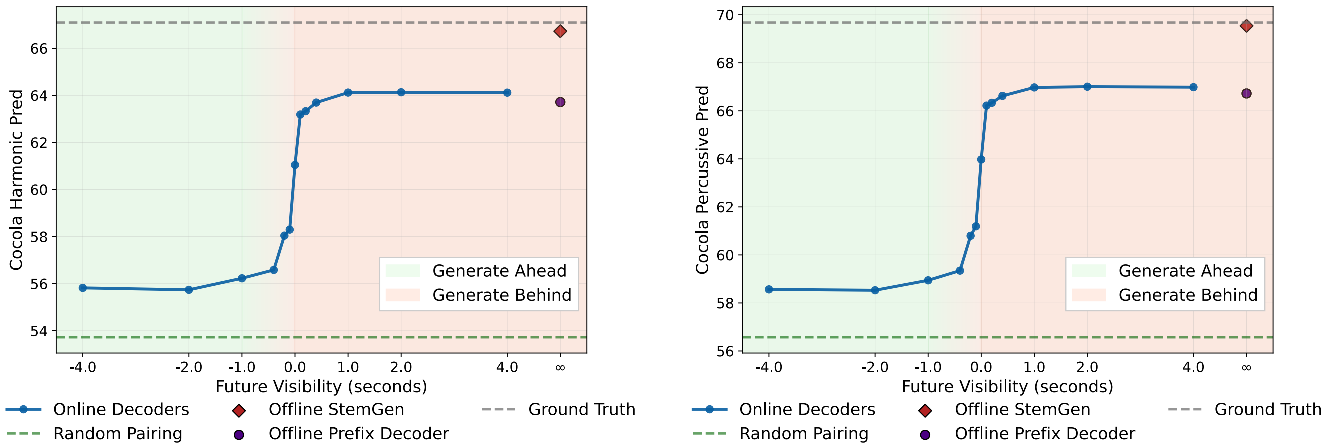
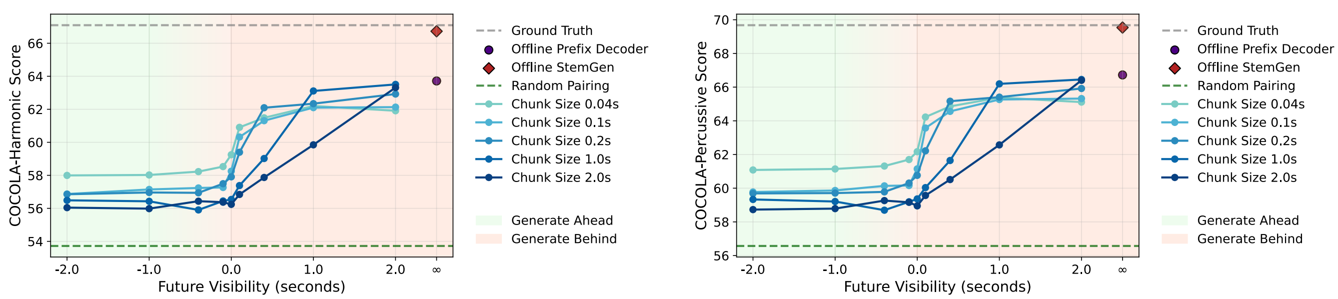


(a) COCOLA Harmonic (b) COCOLA Percussive

Fig. 5. COCOLA harmonic score and COCOLA percussive score of generated accompaniment for streaming models with $k = 1$ across different t_f.



(a) COCOLA Harmonic (b) COCOLA Percussive

Fig. 6. COCOLA harmonic score and COCOLA percussive score of generated accompaniment for streaming models with combinations of $k > 1$ and t_f.

A. APPENDIX

A.1. Dataset Details

When selecting input-output track pairs and a start time for each $10\,\mathrm{s}$ window, we filter by silence and instrument class. We compute A-weighted short-time RMS at $50\,\mathrm{Hz}$ and label frames with level below $-60\,\mathrm{dB}$ as silent. We then reject a window if the input mixture and the target stem do not have at least 50% overlap of non-silent frames. When choosing the target stem, we exclude vocal classes.

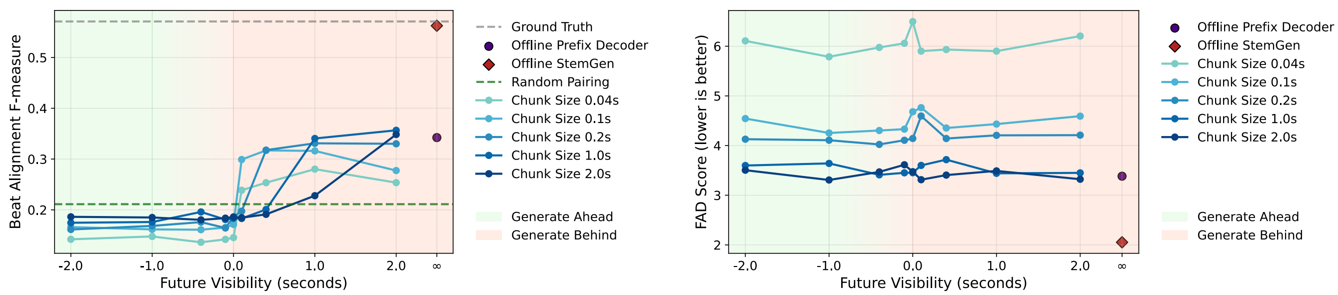
A.2. Transformer Backbone

We use a transformer backbone similar to Llama 3. Following current large-model practice, the network uses pre layer normalization throughout [39], with Root Mean Square Normalization as the normalization operator [40]; we adopt the simplified RMSNorm variant reported to work well at large scale [41]. Positional information is injected by rotary position embedding in self-attention [42]. Inside attention, we apply query-key normalization by normalizing queries and keys along the head dimension before the similarity computation [43], together with a dimension-dependent scaling factor on the normalized scores as recommended by recent scaling results [44]. The feed-forward sublayers use the gated SwiGLU activation [45]. To improve decoding efficiency while preserving quality, key-value projections are shared across groups of query heads, i.e., grouped-query attention [46]. The decoder also supports cross-attention for conditioning on external context.

A.3. Model Implementation Details

For all prefix-decoder models, we do not use a bidirectional mask on the prefix. Instead, we apply a single causal mask over the entire sequence so that every position attends only to past positions.

For the StemGen masked language model, we found a VampNet-style [27] confidence ranking to outperform the original StemGen



(a) Beat Alignment

(b) COCOLA Percussive

Fig. 7. Beat alignment and FAD score of generated accompaniment for streaming models with combinations of $k > 1$ and t_f.

ranking. At each sampling iteration and for each RVQ level, we compute a confidence score for token $\hat{y}_t$ as

$$\mathrm{conf}(\hat{y}_t) \;=\; \log p(\hat{y}_t) \;+\; temp \cdot g_t, \tag{4}$$

where $p(\hat{y}_t)$ is the model probability of $\hat{y}_t$, $g_t \sim \mathrm{Gumbel}(0, 1)$ is i.i.d., and $temp$ is linearly annealed to 0 over the sampling iterations.

A.4. Streaming Prefix Decoder Details

In the streaming setting with chunk size k¿1, we train a prefix decoder. For each minibatch, we sample a prefix length ℓ uniformly from $\{0,\, k,\, 2k,\, \ldots,\, T-k\}$. Given ℓ, we construct each example by aligning inputs and outputs up to step ℓ, then require the model to predict the next k steps $(\ell+1,\, \ldots,\, \ell+k)$ under a causal attention mask. The loss is computed only on these k target steps, and gradients are applied exclusively to those positions, while earlier tokens serve as context without direct supervision. This variable-prefix sampling exposes the model to a range of prefix boundaries and supports chunked next-k prediction during streaming inference.

A.5. Model Sampling Details

For all decoder-only Transformers, we sample with softmax temperature 1.0 and top-$k = 200$. For the StemGen model, we use per-level maximum noise temperatures $[8.0,\ 8.0,\ 4.0,\ 4.0]$ for RVQ levels $\ell = 1, \ldots, 4$, and $[128,\ 64,\ 32,\ 32]$ sampling steps per level. The StemGen model is trained with input dropout probability 20% (the input embedding is zeroed when dropped). At sampling time we use classifier-free guidance with scale 2.0.

For online streaming models, the total input it ever conditioned on is $t_f + T$. That is, if $t_f > 0$, the model see extra input stream, and vice versa.

A.6. Listening Study Details

We ran a listening study in which 24 participants evaluated the models in this study as well as ground truth and random pairing examples. Participants blindly evaluated the models by indicating their preference between pairs of accompaniments for a given input. A Kruskal-Wallis H test and confirmed that there are statistically significant pairs among the permutations. We evaluate significance with a post-hoc analysis using the Wilcoxon signed-rank test with Bonferroni correction (with p¡0.05/21 as there are 7 models evaluated).

To ease the participant's cognitive load, we select samples with six or fewer input tracks for inclusion in the listening test.

	Ground Truth	Offline StemGen	Offline Prefix Decoder	$t_f = 1$	$t_f = 0$	$t_f = -1$	Random Pairing
Ground Truth	N/A	!	*	*	*	*	*
Offline StemGen	!	N/A	!	!	!	*	*
Offline Prefix Decoder	*	!	N/A	!	!	*	!
$t_f = 1$	*	!	!	N/A	!	*	!
$t_f = 0$	*	!	!	!	N/A	*	!
$t_f = -1$	*	*	*	*	*	N/A	!
Random Pairing	*	*	!	!	!	!	N/A

Table 1. Pairwise statistical significance results for listening study. * indicates significant difference ($p < 0.05/21$), ! indicates non-significant ($p > 0.05/21$).

A.7. Audio Mixing

For all objective evaluations and the listening study, we use a fixed loudness pipeline. First, we loudness-normalize the predicted track and the target track to $-18\,\mathrm{dB}$. When forming the mix, all tracks in the input mixture are summed at equal loudness, and the predicted (or target) track is mixed $+5\,\mathrm{dB}$ relative to each input track. Finally, we normalize the resulting mixture to $-18\,\mathrm{dB}$.

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