







SongCreator: Lyrics-based Universal Song Generation

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Introduction



SongCreator: Lyrics-based Universal Song Generation

Song Generation

Generate songs with harmonious and pleasant vocals and accompaniment

Previous works mostly explored specific aspects of song generation, such as vocal composition, instrumental arrangement, and harmonious generation, but none of them is able to combine these three for song generation

- The coordination among various complex elements in vocals and accompaniment poses significant challenges for generating songs as an entity
- The demands for song generation are highly diverse, not only lyrics-to-song generation but also independent vocal or instrumental music generation, song editing, and song generation from a given audio prompt or predetermined track.

Table 1: A comparison of song generation with related tasks in the literature. We use **Composition** to denote whether the model can complete vocal composition, **Arrangement** to denote whether the model can arrange the instrumental accompaniment, and **Harmony** to denote whether vocals and accompaniment sound harmonious and pleasant together.

Tasks	Inputs	Outputs	Composition	Arrangement	Harmony
Singing Voice Synthesis [15-20]	Scores	Vocals	×	×	×
SongComposer [21]	Lyrics	Vocals	1	×	×
Text-to-Music [22-25]	Text Description	Music	×	✓	×
Accompaniment Generation [26-30]	Vocals	Music	×	1	1
Song Generation	Lyrics	Song	1	1	1

Introduction



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Contribution

- Propose a novel dual-sequence language model (DSLM) for song generation, which not only emphasizes the respective quality of vocals and accompaniment but also learns their mutual influences to coordinate them into harmonious songs
- Propose a series of attention mask strategies, which enables our model to complete song generation tasks of various forms, such as editing, understanding, and generation
- Based on the above mechanism, we propose a versatile system for song generation named SongCreator
 - Support universal conditioning and generation for eight tasks
 - > Achieving state-of-the-art or competitive performances on all tasks

Tasks	Conditions	Outputs
Lyrics-to-song*	Lyrics, [Vocal prompt], [Accompaniment prompt]	Song, Vocals
Lyrics-to-vocals*	Lyrics, [Vocal prompt]	Vocals
Accompaniment-to-song	Lyrics, Accompaniment, [Vocal prompt]	Song, Vocals
Vocals-to-song	Vocals, [Lyrics], [Accompaniment prompt]	Song, Music
Music continuation	Accompaniment prompt	Music
Song editing*	Lyrics, Vocals, Accompaniment	Song, Vocals
Vocals editing	Lyrics, Vocals	Vocals
Vocals editing in song*	Lyrics, Vocals, Accompaniment	Song, Vocals

Methodology



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Overall Model

- BEST-RQ: Self-supervised learning model to obtain the semantic tokens from audio, which encapsulates sufficient semantic and acoustic details that are necessary for reconstructing
- DSLM: The "brain" of our system for predicting the semantic token of songs from a variety of optional inputs, including lyrics, vocal prompt, accompaniment prompt, pre-determined vocal track, and pre-determined accompaniment track
- LDM: Decode the semantic tokens into high-quality song audio

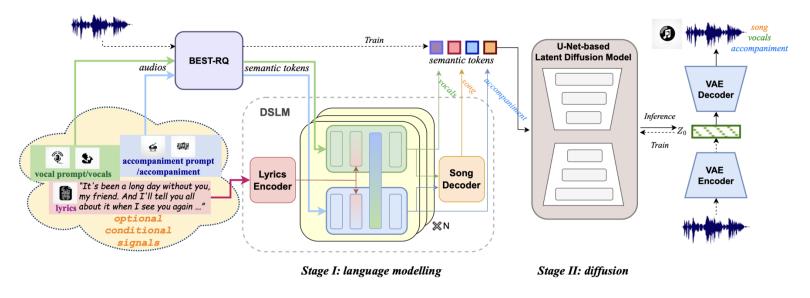


Figure 1: The overview of SongCreator. The BEST-RQ tokens is a proxy that bridges the DSLM and the latent diffusion model.

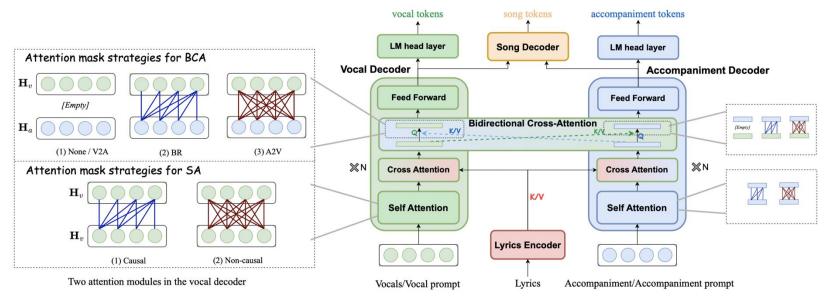
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Dual-Sequence Language Model (DSLM)

- A lyrics encoder to extract critical information related to the pronunciation of the lyrics
- Two decoders to autoregressively generate semantic tokens for the vocals and accompaniment, respectively
 - > Utilize the cross-attention layer to attend the information from the lyrics encoder
 - Utilize the bidirectional cross-attention (BCA) layer to capture and model the complex interrelationship between vocals and accompaniment
- A final song decoder to non-autoregressively generate semantic tokens for songs



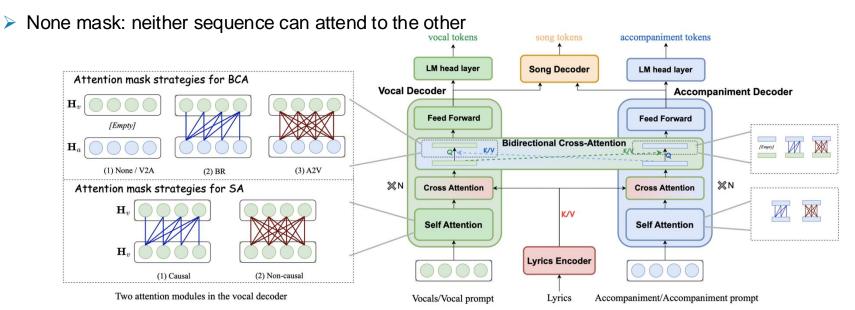
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Attention mask strategies for DSLM

- □ For Self-Attention (SA)
 - > Causal attention mask: each token can only access the leftward context tokens and itself
 - > Non-causal attention mask: all tokens can attend to each other within the same sequence
- For Bidirectional Cross-Attention (BCA)
 - > Bidirectional (BR) mask: tokens in each sequence can attend to the tokens in the other sequence that occur at earlier positions
 - Accompaniment-to-Vocals (A2V) and Vocals-to-Accompaniment (V2A) mask: tokens in one sequence can attend to all tokens in the other sequence



Experiments



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The result of tasks

- SongCreator achieves state-of-the-art or competitive performances on all tasks
- SongCreator can better maintain the acoustic conditions from prompt and can independently control the vocals and accompaniment in the generated songs
- humans judge the edited song produced by SongCreator to be as natural as the original unedited song

Table 9: Music continuation evaluation.

Model	$ $ FAD \downarrow	Musicality †	Similarity \uparrow
Ground Truth	-	3.9 ± 0.11	3.70 ± 0.10
AudioLM	1.33	3.95 ± 0.10	3.78 ± 0.08
GPT	1.28	3.90 ± 0.10	3.73 ± 0.11
SongCreator	1.54	3.97 ± 0.08	3.83 ± 0.08

Table 3: Lyrics-to-song evaluation without audio Table 4: Lyrics-to-vocals evaluation without audio prompt prompt

prompt.				prompt.		
Model	\mid FAD \downarrow	Musicality \uparrow	Quality \uparrow	Model	\mid Musicality \uparrow	Quality \uparrow
Ground Truth	-	4.3 ± 0.04	4.09 ± 0.05	Ground Truth	$\mid 3.89\pm0.09$	3.91 ± 0.07
MusicLM MusicGen GPT	6.47 2.31 8.18	3.21 ± 0.09 3.08 ± 0.06 3.32 ± 0.10	3.25 ± 0.07 2.99 ± 0.06 3.26 ± 0.08	MusicLM VALL - E GPT	$\begin{vmatrix} 3.31 \pm 0.06 \\ 3.15 \pm 0.08 \\ 3.64 \pm 0.07 \end{vmatrix}$	$\begin{array}{c} 3.35 \pm 0.06 \\ 3.23 \pm 0.06 \\ 3.58 \pm 0.07 \end{array}$
GPT (Vocals & Song) SongCreator	11.23	3.55 ± 0.09 4.25 ± 0.05	3.64 ± 0.07 4.08 ± 0.06	SongCreator SongCreator (Vocal Only)	$\begin{vmatrix} 3.98 \pm 0.04 \\ 3.68 \pm 0.06 \\ 2.52 \pm 0.06 \end{vmatrix}$	3.79 ± 0.05 3.63 ± 0.05
SongCreator (Single)	3.04	3.85 ± 0.06	3.75 ± 0.05	SongCreator (Single)	$ 3.53 \pm 0.06$	3.64 ± 0.05

Table 5: Prompt-based lyrics-to-song. We sample	e Table 6: Prompt-based lyrics-to-vocals. We sample
the prompt at random from a held-out set.	the prompt at random from a held-out set.

FAD \downarrow	$\mathbf{MCD}\downarrow$	Musicality \uparrow	Similarity †
-	-	4.04 ± 0.06	3.79 ± 0.09
1.90 2.06	9.78 8.44	3.46 ± 0.11	3.27 ± 0.11 3.82 ± 0.08
	- 1.90 2.06	 1.90 9.78	$\begin{array}{c ccccccccccccccccccccccccccccccccccc$

Model SECS 1 Musicality \uparrow Similarity **↑** Ground Truth 0.62 3.63 ± 0.08 3.57 ± 0.08 VALL - E 0.66 3.34 ± 0.07 3.30 ± 0.08 SongCreator 0.68 $\mathbf{3.57} \pm \mathbf{0.06}$ $\mathbf{3.55} \pm \mathbf{0.07}$

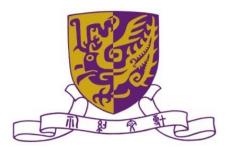
Table 7: Vocals-to-song evaluation.

Table 8: Accompaniment-to-song evaluation.

Model	\mid FAD \downarrow	Musicality \uparrow	Harmony \uparrow	Model	\mid FAD \downarrow	$\textbf{Musicality} \uparrow$	Harmony \uparrow
Ground Truth	-	4.12 ± 0.05	3.91 ± 0.08	Ground Truth	-	4.15 ± 0.07	4.11 ± 0.07
SingSong SingSong (Diffusion) GPT	3.37 4.13 3.07	$\begin{array}{c} 3.67 \pm 0.10 \\ 3.71 \pm 0.08 \\ 3.73 \pm 0.07 \end{array}$	$\begin{array}{c} 3.63 \pm 0.08 \\ 3.67 \pm 0.06 \\ 3.69 \pm 0.07 \end{array}$	SingSong SingSong (Diffusion) GPT	1.82 2.98 1.64	$\begin{array}{c} 3.36 \pm 0.06 \\ 3.66 \pm 0.06 \\ 3.53 \pm 0.08 \end{array}$	$\begin{array}{c} 3.42 \pm 0.07 \\ 3.65 \pm 0.05 \\ 3.53 \pm 0.09 \end{array}$
SongCreator SongCreator (Single)	1.88 1.46	$\begin{array}{c} 3.77 \pm 0.08 \\ 3.58 \pm 0.08 \end{array}$	$\begin{array}{c} {\bf 3.77 \pm 0.07} \\ {\bf 3.65 \pm 0.06} \end{array}$	SongCreator SongCreator (Single)	1.24 1.23	$\begin{array}{c} 3.67 \pm 0.05 \\ 3.60 \pm 0.07 \end{array}$	$\begin{array}{c} 3.78 \pm 0.06 \\ 3.62 \pm 0.06 \end{array}$

Table 10: Song editing evaluation.

Table 11: Vocals editing evaluation. Model **FAD** \downarrow **MCD** \downarrow **Musicality** \uparrow Model SECS ↑ Musicality \uparrow Naturalness ↑ Naturalness ↑ Ground Truth 4.08 ± 0.07 3.99 ± 0.06 Ground Truth 3.65 ± 0.08 3.45 ± 0.07 ---GPT 2.29 8.30 3.84 ± 0.07 3.72 ± 0.06 GPT 0.87 3.64 ± 0.07 $\mathbf{3.43} \pm \mathbf{0.07}$ $\mathbf{3.78} \pm \mathbf{0.07}$ SongCreator 7.90 $\mathbf{4.01} \pm \mathbf{0.06}$ 0.87 $\mathbf{3.68} \pm \mathbf{0.06}$ 3.31 ± 0.06 1.81SongCreator SongCreator (Single) 1.877.85 3.93 ± 0.08 3.75 ± 0.08 SongCreator (Single) 0.87 3.63 ± 0.06 3.41 ± 0.06









Thanks!



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Listen to Samples