



AI-Lyricist:

Generating Music and Vocabulary Constrained Lyrics

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Language Learning via Singing

- Singing benefits learning foreign languages. •
- **SLIONS**: transforming this idea into practice: •

Watching pre-recorded song videos;

Singing songs following the teacher's examples;



- [1] Dania Murad, Riwu Wang, Douglas Turnbull, and Ye Wang. 2018. SLIONS: A Karaoke Application to Enhance Foreign Language Learning. In 2018 ACM Multimedia Conference on Multimedia Conference. ACM, 1679-
- [2] Dwayne Engh. 2013. Why Use Music in English Language Learning? A Survey of the Literature. English Language Teaching 6, 2 (2013), 113–127.
- [3] Douglas Fisher. 2001. Early language learning with and without music. Reading Horizons 42, 1 (2001), 39.
- [4] Arla J Good, Frank A Russo, and Jennifer Sullivan. 2015. The efficacy of singing in foreign-language learning. Psychology of Music 43, 5 (2015), 627–640.
- [5] Suzanne L Medina. 1990. The Effects of Music upon Second Language Vocabulary Acquisition. (1990).
- [6] Susan Bergman Miyake. 2004. Pronunciation and music. Sophia Junior College Faculty Bulletin 20, 3 (2004), 80.
- [7] Andrés Roberto Rengifo. 2009. Improving pronunciation through the use of karaoke in an adult English class. Profile Issues in Teachers Professional Development 11 (2009), 91–106.
- [8] Wanda T Wallace. 1994. Memory for music: Effect of melody on recall of text. Journal of Experimental Psychology: Learning, Memory, and Cognition 20, 6 (1994), 1471.
- [9] Judith Weaver Failoni. 1993. Music as Means To Enhance Cultural Awareness and Literacy in the Foreign Language Classroom. Mid-Atlantic Journal of Foreign Language Pedagogy 1 (1993), 97–108.

Limitations





Songs with suitable lyrics may not match users' music preferences.

Lyrics do not match learners' linguistic ability and learning objectives.

Problem Statement

- Generating **novel** yet **meaningful** lyrics that match the users' :
 - language level (mastered vocabulary) and learning objectives (new words);
 - music interests (reflected by a MIDI file they prefer).







Music Structure Analyzer







Lyrics Generator: Syllable Awareness





Syllable Planning:

Input: How many syllables the remaining sentence should have? Output: How many syllables the remaining sentence should have after picking this word?



Deep-coupled Music-Lyrics Embedding



Deep-coupled Music-Lyrics Embedding



[1] Bei Liu, Jianlong Fu, Makoto P Kato, and Masatoshi Yoshikawa. 2018. Beyond narrative description: Generating poetry from images by multi-adversarial training. In 2018 ACM Multimedia Conference on Multimedia Conference. 783-791...

Deep-coupled Music-Lyrics Embedding







Experiment: Objective Evaluation

Novelty $-n = m_{n_{IF}}/m_n$ How often the generator uses infrequent words/phrases?

 $Dist - n = m_{n_U}/m_n$

Relevance

BLEU

Application – oriented Satisfaction Info Density: How many unique words/phrases are used?

The music-lyrics relevance calculated by the deep-coupled embedding model.

Text quality.

Whether the generated lyrics is singable? Containing keywords and matching vocabulary constraints?

Experiment: Subjective Evaluation

Participants: 60 native English speakers

Platform: Amazon MTurk

Procedures:

(1) A participant **reads the lyrics** generated from the same music by the 5 compared models and **rates the lyrics** on a 0-5 scale regarding their fluency, coherence, meaningfulness and poetic aesthetics respectively.

(2) A participant **listens to a singing sample** synthesized with the music and lyrics generated by the 5 models, and **rates the lyrics** on a 0-5 scale regarding the syllable alignment to the melody and their relevance respectively.

Experiment: Results

a. Objective Evaluation	Novelty-2	Novelty-3	Dist-1	Dist-2	BLEU-1	BLEU-2	BLEU-3	Relevance	Overall	App Satisfac	o ction
МТ	0.390	0.190	9.16e-2	0.254	0.22	1.09e-2	3.71e-7	66.52	0.538	Ν	
ED	6.02e-3	1.07e-3	4.81e-2	0.980	0.03	2.55e-5	1.53e-6	60.67	0.187	Ν	
SeqGAN	5.21e-2	8.5e-2	0.132	0.417	0.17	9.61e-3	5.25e-4	68.22	0.554	Ν	
PRE-M2L-B	0.410	0.213	6.82e-3	0.135	0.26	1.40e-2	3.30e-4	66.13	0.590	Y	
POST-M2L	1.97e-4	0.0	0.164	0.363	1.92e-3	3.53e-6	~0.0	59.03	0.159	Ν	
POST-M2L-S	8.09e-2	0.330	0.115	0.251	3.91e-2	3.47e-3	4.31e-4	68.84	0.482	Y	
POST-M2L-T	0.224	0.144	0.150	0.473	3.67e-2	2.28e-3	6.61e-5	74.82	0.464	Y	
POST-M2L-B	0.169	0.158	0.108	0.406	0.21	1.08e-2	3.36e-4	70.59	0.601	Y	
b. Subjective Evaluation	Fluency		Coherence	Meaningfulness		Aesthetics	Syllable Alignment	Relevan	ice	Overall	
МТ	2.43		2.40	2.60		2.47	2.87	2.87		2.61	
ED	2.87		2.83	2.6		2.87	3.43	2.77		2.90	
SeqGAN	2.83		2.80	2.63		2.67	3.23	3.00		2.86	
PRE-M2L-B	3	3.67		3.46		3.40	4.00	3.67		3.59	
POST-M2L-B	4.37		4.47	4.37		4.17	4.53	4.50		4.40	J

Demo: Auto Mode & Interactive Mode



Input MIDI: Imagine.mid Keywords: ["know" , "see"] Interactive Mode

Automatic mode: Generating the whole piece of lyrics

Interactive mode: Generating sentence by sentence. The user chooses one sentence from top 5 candidates.

Summary

First attempt to generate lyrics that match both the style and syllable pattern of multi-channel music.

Utilize a SeqGAN based generator to generate meaningful and coherent lyrics approaching human songwriting.

Propose Polisher module to constrain lyrics generation with mandatory keywords and a vocabulary set.

Thank you!

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