

ScripTONES: Sentiment-Conditioned Music Generation for Movie Scripts





Vishruth Veerendranath^{1,2}, Vibha Masti^{1,2}, Utkarsh Gupta¹, Hrishit Chaudhuri¹, Gowri Srinivasa¹





¹PES Centre for Pattern Recognition, PES University ²Carnegie Mellon University

Problem Statement

- Film score essential for cinematic experience
- Automated system for generating emotionaligned symbolic music
- Two components:
 - Movie script (text) encoder
 - Music generator decoder
- Quantifying emotion: valence-arousal [1]
 - Text: NRC VAD lexicon [2]
 - Music: EMOPIA [3]
 - Piano midi snippets tagged with quadrant of VA [4]

Attribute Vector Arithmetic

- Attribute vector arithmetic in VAEs extended to MusicVAE
- Four attribute vectors: high valence (z_{vh}) , low valence (z_{vl}) , high arousal (z_{ah}) , and low arousal (z_{al})
- Averaging out latent vectors of EMOPIA samples encoded with MusicVAE.

$$z_{ec} = \begin{cases} |V| * z_{vh} + |A| * z_{ah} & (V \ge 0, A \ge \alpha) \\ |V| * z_{vh} + |A| * z_{al} & (V \ge 0, A < \alpha) \\ |V| * z_{vl} + |A| * z_{ah} & (V < 0, A \ge \alpha) \\ |V| * z_{vl} + |A| * z_{al} & (V < 0, A < \alpha) \end{cases}$$

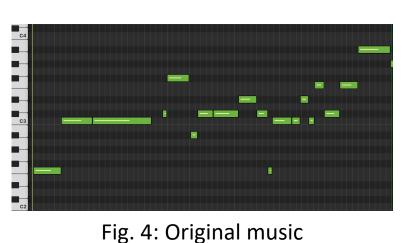




Fig. 5: Modified with increased valence

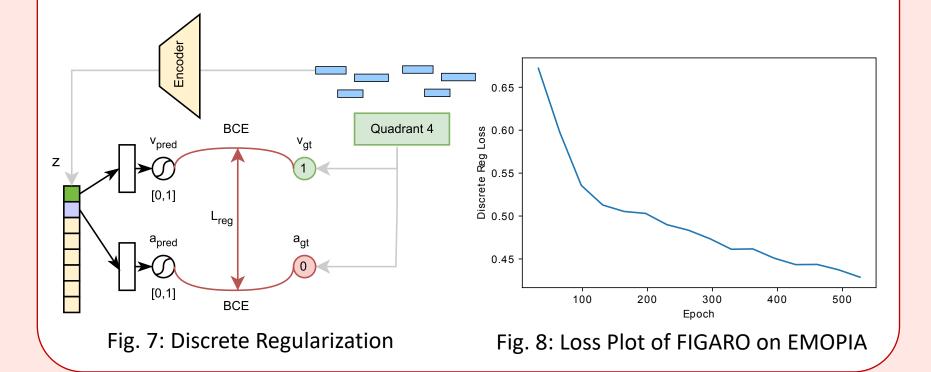


Fig. 6: Modified with increased arousal

Discrete Regularization

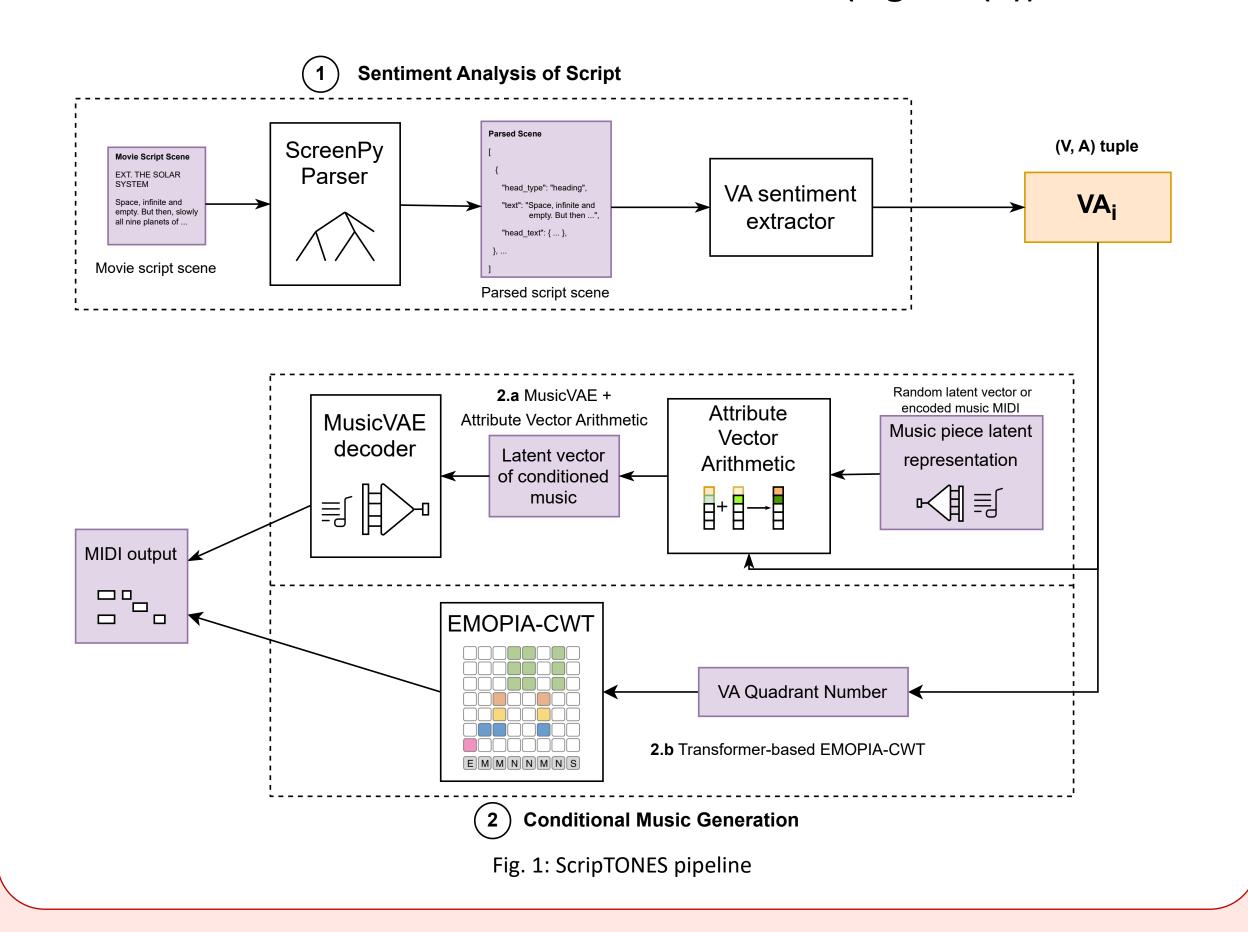
- Improving sentiment conditioning in VAEs
- Regularizing 2 latent dimensions to encode valence & arousal
- Finetune pretrained FIGARO [5] VAE on EMOPIA data as per loss below

$$L_{req_{disc}} = BCE(v_{pred}, v_{qt}) + BCE(a_{pred}, a_{qt})$$



Methodology

- Two-phase pipeline for sentiment-conditioned music generation
- Sentiment analysis of movie script
 - Unweighted average
- Conditional music generator experimented with two different techniques
 - EMOPIA-CWT (Transformer-based) (Fig. 1 2(b))
 - MusicVAE with attribute vector arithmetic (Fig. 1 2(a))



User Study Evaluation

- Survey on 31 users with varying musical knowledge
- 3 different movie scene demos, two different music pieces (EMOPIA-CWT and MusicVAE)
- For each piece, rate on a scale of 1-4:
 - 1. Valence/positivity 2. Arousal/excitement 3. Overall mood fit

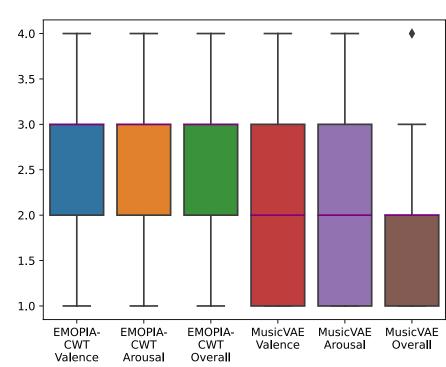


Fig. 2: Box-plot of user ratings for E-CWT & MVAE models

Music Knowledge Rating

Fig. 3: Music Knowledge rating of survey subjects

Table 1: Average ratings of match between generated music and film scene

Attribute Rated	E-CWT	MVAE
Valence	2.62	1.96
Arousal	2.44	1.92
Overall Mood Fit	2.48	1.86

Representations (2023).

Table 2: User evaluated scene-wise overall mood fit ratings on a scale of 1-4

Scene Number	E-CWT	MVAE
Scene 1	2.52	1.58
Scene 2	1.87	2.17
Scene 3	3.06	1.84

References

- Jonathan Posner, James A Russell, and Bradley S Peterson. The circumplex model of affect: An integrative approach to affective neuroscience, cognitive development, and psychopathology. Development and psychopathology, 17(3):715–734, 2005.
- 2. Saif M. Mohammad. Obtaining reliable human ratings of valence, arousal, and dominance for 20,000 english words. In Proceedings of The Annual Conference of the Association for
- Computational Linguistics (ACL), Melbourne, Australia, 2018. 3. Hsiao-Tzu Hung, Joann Ching, Seungheon Doh, Nabin Kim, Juhan Nam, and Yi-Hsuan Yang. Emopia: A multi-modal pop piano dataset for emotion recognition and emotion-based music
- generation. arXiv preprint arXiv:2108.01374, 2021 4. Yu, Liang-Chih, Lung-Hao Lee, Shuai Hao, Jin Wang, Yunchao He, Jun Hu, K. Robert Lai, and Xuejie Zhang. "Building Chinese affective resources in valence-arousal dimensions." In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pp. 540-545. 2016. Rütte, Dimitri von, Luca Biggio, Yannic Kilcher and Thomas Hofmann. "FIGARO: Controllable Music Generation using Learned and Expert Features." International Conference on Learning