Language-Guided Music Recommendation for Video via Prompt Analogies

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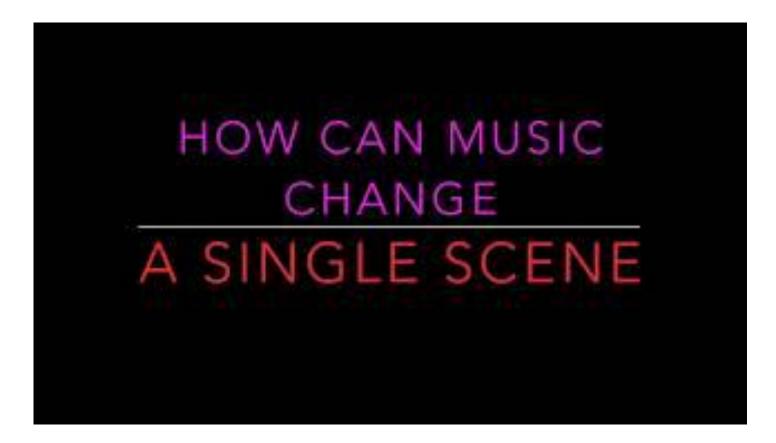
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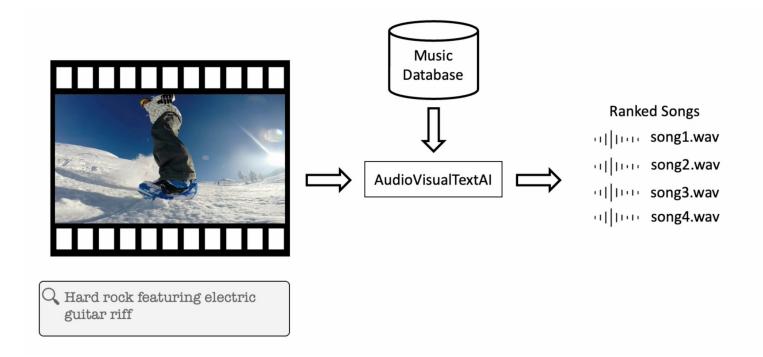
Same scene different music



Introduction

- Music selection can transform a scene into one that is perceived as urgent, sad ...
- In previous work, music is retrieved based solely on the visual content from video.
- This paper propose a user guided music-for-video recommendation approach.

Overview



• There are no available datasets which include music, video, and text together

• The existing datasets that do include text and music focus on a limited vocabulary of tags rather than free-form text. (e.g. electronic, acoustic guitar..)

• It is expensive to obtain high-quality human descriptions.

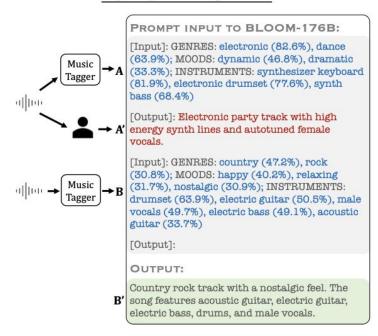
I. prompt2text Synthesis PROMPT INPUT TO BLOOM-176B: [Input]: GENRES: electronic (82.6%), dance (63.9%); MOODS: dynamic (46.8%), dramatic Music →A (33.3%); INSTRUMENTS: synthesizer keyboard **Tagger** (81.9%), electronic drumset (77.6%), synth bass (68.4%) [Output]: Electronic party track with high energy synth lines and autotuned female vocals. [Input]: GENRES: country (47.2%), rock (30.8%); MOODS: happy (40.2%), relaxing →R (31.7%), nostalgic (30.9%); INSTRUMENTS: Music drumset (63.9%), electric guitar (50.5%), male vocals (49.7%), electric bass (49.1%), acoustic guitar (33.7%) [Output]: **OUTPUT:** Country rock track with a nostalgic feel. The B' song features acoustic guitar, electric guitar, electric bass, drums, and male vocals.

II. data2text Synthesis Music Tagger GENRES: country. MOODS: happy, INSTRUMENTS: drumset. relaxing, nostalgic male vocals, acoustic guitar rock **Input Tags into Template Sentences** The music gives a The soundtrack has This is country and happy, relaxing and drumset, male vocals, and rock music. nostalgic vibe. acoustic guitar. Zero-shot D2T Pipeline: Ordering, Aggregation, and Compression This is country and rock music. The soundtrack has acoustic guitar, drumset, and male vocals giving a happy, relaxing, and nostalgic vibe. III. tags Synthesis acoustic guitar, country, happy, drumset, Music relaxing, electric bass, male vocals, rock, Tagger nostalgic, electric guitar

- **I**.prompt2text
 - : Combining a pre-trained music tagger and human annotation with a large-scale language model.

- LLM: Bloom-176B*
- Music Tagger**

I. prompt2text Synthesis



^{*} BLOOM (Scao et al., 2022) /https://huggingface.co/bigscience/bloom

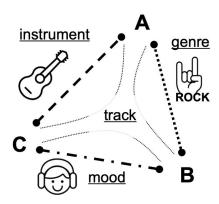
^{**} Disentangled multidimensional metric learning for music similarity (Lee et al., 2020)

• **I**.prompt2text

: Combining a pre-trained music tagger

and human annotation

with a large-scale language model.



LLM: Bloom-176B*

Music Tagger**: 41 instrument tags, 20 genre tags, 28 mood tags

keeping only those above a threshold(0.3 in this paper)

^{*} BLOOM (Scao et al., 2022) / https://huggingface.co/bigscience/bloom

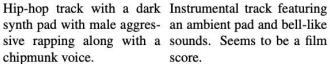
^{**} Disentangled multidimensional metric learning for music similarity (Lee et al., 2020)

Dataset: YouTube8M - Music Video

- Music sampled 10 seconds audio clips from middle of each music video.
- An annotation describes only the music from YT8M sample, Annotators do not see the corresponding video.

3,000 for test, 1,000 for training







score.

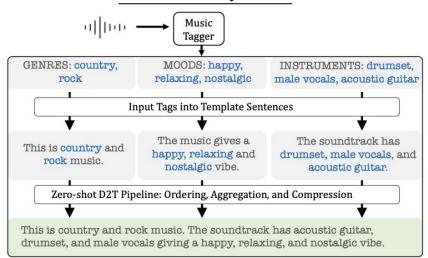
• **II**:data2text Synthesis

: Using Zero-shot D2T approach*

• **III**.tags Synthesis

: Shuffling tags randomly

II. data2text Synthesis

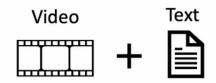


III. tags Synthesis



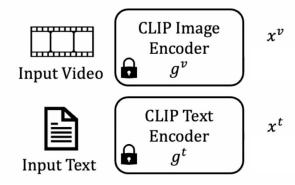
^{*} Neural pipeline for zero-shot data-to-text generation (Kasner et al., 2022)

Balancing Influence of Video/Text Inputs for Audio Retrieval

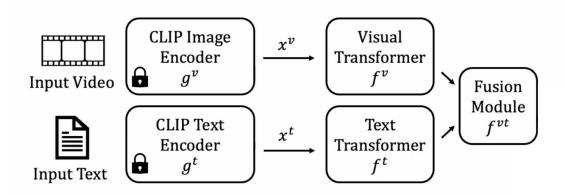


- Propose a video+text fusion model architecture
- Using text dropout to prevent overfitting on text

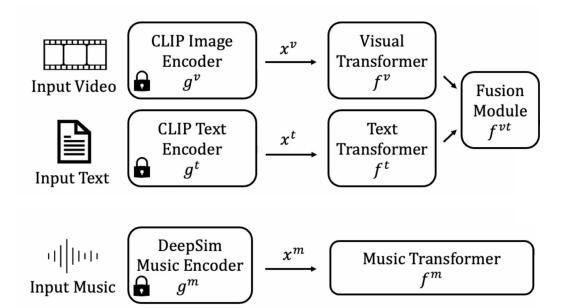
- Split the video into 10-second segments(6 frames per second) and get features using CLIP ViT-B/32.
 Compute a feature by averaging CLIP embedding features.
- Get text feature from input text using CLIP.



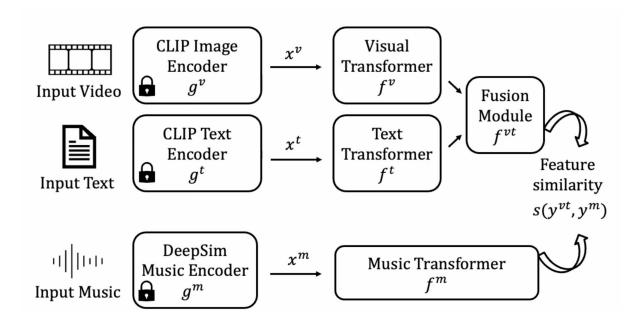
- Input feature to each modality transformer encoders, and combined video and text embedding.
- Get fused embedding from the fusion model.



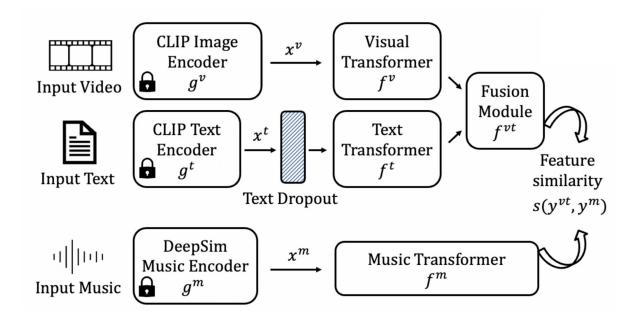
- Extract music feature using Music Encoder and get music embedding using music transformer
- DeepSim → Tagger



- Get feature similarity between fusion embedding(video-text) and music embedding.
- But the model starts overfitting to the training text input ...



- With probability p(0.8), set the input text embedding x^t to a specific value x^{NULL}
- It yields improving the performance

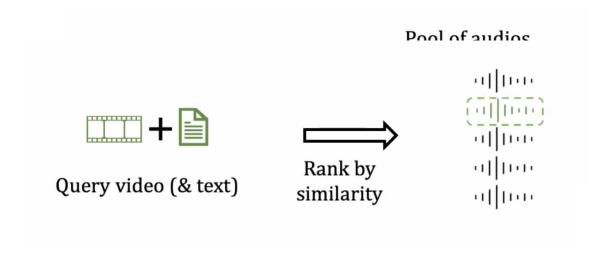


- Use InfoNCE loss between music and fused video-text embeddings.
- τ is hyperparameter (0.03 in this paper), similarity metric is cosine similarity.

Loss is not symmetric, so final loss is summed loss.

$$\mathcal{L}_{vt \to m} = -\frac{1}{|\mathcal{D}|} \sum_{i \in \mathcal{D}} \mathcal{L}_{m,vt} = \mathcal{L}_{vt \to m} + \mathcal{L}_{m \to vt}$$

$$\mathcal{L}_{j \in \mathcal{D}} \leftarrow \mathcal{L}_{j \in \mathcal{D}} \leftarrow \mathcal{L}_{vt \to m} + \mathcal{L}_{m \to vt}$$
Feature similarity
$$s(y^{vt}, y^m)$$



- The poll of N music, N=2000 in track level and N=500 for evaluation clips
- Recall metric

Method	Train Text	Query Text Input	Median Rank ↓	R@1↑	R@5↑	R@10↑
a. Pretét et al. [31]	-	040	234	0.76	3.42	5.90
b. MVPt [36]	-	(-)	13	6.09	24.91	41.89
c. MVPt+ [36]	23	121	5	27.93	50.64	60.68
d. ViML (ours)	tags	(2)	3	29.43	62.49	75.40
e. ViML (ours)	tags	tags	2	49.49	81.61	89.41
f. Chance			1000	0.05	0.25	0.50

- Tag-based music retrieval on full YoTube8M-MusicVideo
- MVTPt+ is improved version of MVP (tuned the parameter τ in the InfoNCE loss to 0.03 from 0.3)

^{*} Cross-modal music-video recommendation(Pretet et al., 2021)

^{**} It's time for artistic correspondence in music and video(Suris et al. 2022)

Method	Train Text	$MR \downarrow$	R@1↑	R@5↑	R@10↑
a. MVPt+	=	17	12.20	29.43	40.46
b. ViML	tags	15	11.95	30.34	42.62
c. ViML	data2text	13	13.61	33.94	46.24
d. ViML	prompt2text	12	14.09	35.04	47.88
Chance		250	0.20	1.00	2.00

- Music retrieval on YT8M-MusicTextClips
- Video includes only a 30sec clip surrounding the 10sec of audio labeled by human annnotato

Method	Train Text	Dropout	Text Inputs	Median Rank ↓	R@1↑	R@5↑	R@10↑
a. MVPt+	·	11=11	83	17	12.20	29.43	40.46
b. ViML	prompt2text	Х	95	20	9.94	26.42	37.01
c. ViML	prompt2text	X	human	15	11.45	30.45	42.77
d. ViML	prompt2text	/	(-	16	12.27	30.34	41.51
e. ViML	prompt2text	1	human	12	14.09	35.04	47.88

- Performance of with and without text dropout
- Dropout technique is most effective in the range of 0.8 0.95

Output











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Thank you