

# V2Meow: Meowing to the Visual Beat via Music Generation

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## Abstract

*Generating high quality music that complements the visual content of a video is a challenging task. Most existing visual conditioned music generation systems generate symbolic music data, such as MIDI files, instead of raw audio waveform. Given the limited availability of symbolic music data, such methods can only generate music for a few instruments or for specific types of visual input. In this paper, we propose a novel approach called V2Meow that can generate high-quality music audio that aligns well with the visual semantics of a diverse range of video input types. Specifically, the proposed music generation system is a multi-stage autoregressive model which is trained with a number of  $O(100K)$  music audio clips paired with video frames, which are mined from in-the-wild music videos, and no parallel symbolic music data is involved. V2Meow is able to synthesize high-fidelity music audio waveform solely conditioned on pre-trained visual features extracted from an arbitrary silent video clip, and it also allows high-level control over the music style of generation examples via supporting text prompts in addition to the video frames conditioning. Through both qualitative and quantitative evaluations, we demonstrate that our model outperforms several existing music generation systems in terms of both visual-audio correspondence and audio quality.*

## 1. Introduction

The emotional impact of visual representation can be significantly enhanced by the addition of music, whether it be in a movie, advertisement, or video blog. For instance, a sad scene can be effectively complemented by a slower, melancholic piece, while an action scene may better match with more energetic and fast-paced music. Both music and visual

art are powerful ways of expressing ourselves and communicating with others, and when they are used together, we can create a truly immersive artistic experience. Modern technology allows anyone to create videos and produce their own visual art on a mobile phone. However, creating the right background music with the desired groove to complement the video remains a challenge. Can we enable video creators to generate their own background music through video input alone? How can we learn the audio-visual semantic correspondence from existing music videos to create music conditioned on visual inputs? Can we further empower users to control the generated music using text prompts?

In recent years, notable progress has been made in generating natural sound given video input that is faithful to the audio events in the silent video [39, 54, 9]. While these tasks rely on the intrinsic physical correspondence between the audio and video, such relationships are not the only major factor determining the correspondence between music and video. Videos could also be paired with a music that has the right *feel* to enrich the video content. More recent works extend automatic audio generation to music generation from silent videos using deep learning methods [14, 20, 44, 46]. Most works learn a mapping from visual inputs to a symbolic music representation, i.e. the Musical Instrument Digital Interface (MIDI) data, followed by a MIDI-synthesizer to produce the final audio. While symbolic-representation-based methods can generate music with desirable acoustic properties, by design they cannot express complex and nuanced music which is aligned with music listener’s preferences, and thus limit the creative power. In addition, the MIDI-based generation approaches are hard to scale, as they cannot leverage the vast amount of parallel music and video data available on the internet.

A series of recent works have shown promising results on modeling unconditional audio generation directly on the waveform level [13, 5], which opens up new possibilities to generate music with quality comparable to human-made music. In particular, AudioLM is a multi-stage autoregressive modeling approach to audio generation which uses a masked language model pre-trained on tokenized audio encodings to

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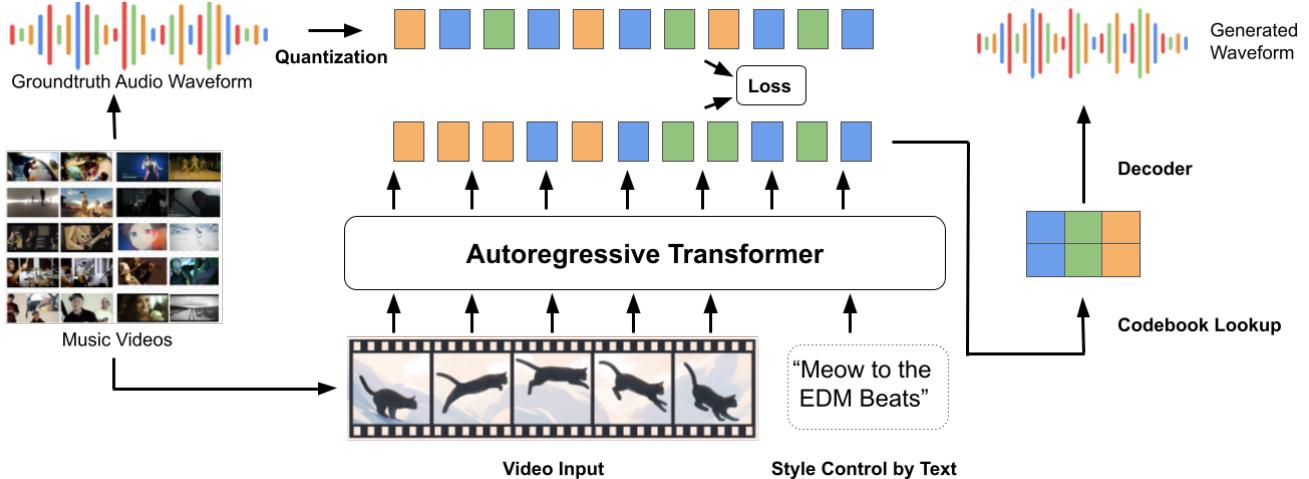


Figure 1: The video to music generation model V2Meow synthesizes high-fidelity music conditioned on video input and optionally text describing high-level style.

capture long-term structure and the discrete codes produced by a neural audio codec to achieve high-quality synthesis. While MusicLM [2], Mubert [35] and SingSong [15] further showed that autoregressive model can generate music conditioned on text prompts or input vocal [15], Riffusion [19], Noise2Music [27] and other recent work [34] have shown that diffusion models are capable of generating high-quality music with text control.

We propose *V2Meow*, a novel pipeline for generating high-fidelity music audio waveforms conditioned on silent video input. Inspired by MusicLM [2], we take a multi-stage autoregressive language modeling approach to condition music generation on both video and text prompts. Compared to previous video to music retrieval model proposed in [47], V2Meow leverages generative models instead to explore a wider music latent space, to further understand the human intuition of the non-physical and often *artistic* connection between music and video by investigating various visual representations as inputs. V2Meow enables additional high-level control over the style of the generated music through text prompt, by incorporating a recent music-text joint embedding model, MuLan [26]. Compared to MusicLM, which also relies on MuLan to learn the text to music mapping, the focus of V2Meow is to understand what additional creative value can be offered by video prompts in addition to text prompts. We summarize our contributions as follows:

- We propose a visually conditioned music generation system, V2Meow, that can generate high-fidelity music audio from silent videos. To the best of our knowledge, we are the first work for training video-to-music generation without the need for MIDI data.
- Our framework allows for incorporating different pre-trained visual feature extractors in a plug-in manner which enables us to generate music for a diverse range of video

content as input with an optional text control.

- We establish quantitative and qualitative measures to evaluate music-video correspondence between video input and generated music, and present extensive empirical results to understand the connection between different semantic and temporal video features and diverse music genres.
- Both numerical and human study results show that, compared to the MIDI-based music generation baseline, V2Meow can produce high-fidelity music better aligned with human music preference, and by allowing video as input, V2Meow can produce music aligned with visual content compared to using text-only input.

## 2. Related Work

### 2.1. Video to Audio

In recent years, several deep learning approaches have been developed for sound synthesis for silent videos. Owens *et al.* [39] investigated predicting the sound emitted by interacting objects with a drumstick. They adopted a neural network to predict sound features and then performed an exemplar-based retrieval algorithm instead of directly generating the sound. Chen *et al.* [8] proposed to use conditional generative adversarial networks for cross-modal generation on lab-collected music performance image-sound pairs. Zhou *et al.* [54] introduced a SampleRNN-based method to directly predict a waveform from an unconstrained video dataset that contains 10 types of sound recorded in the wild. Chen *et al.* [7] proposed a perceptual loss to improve the audio-visual semantic alignment. Chen *et al.* [9] introduced an information bottleneck to generate visually aligned sound. The performance of these video to audio generation models are largely limited by the usually weak correspondence between the video and audio, and the small scale training

data. Without a powerful audio generative model and audio representations, it is challenging to generate high quality audio given a silent video.

## 2.2. Video to Music

In addition to environment sounds, several works have explored generation of music from videos. Direct music generation approaches have been developed for videos capturing a musician playing an instrument [31, 44, 20]. A ResNet-based method was proposed in [31] to predict the pitch and the onsets events given video frames of top-view videos of pianists playing the piano. Later, Audeo [44] demonstrated the possibility of transcribing pianist videos to high-quality music by leveraging the symbolic music representation (MIDI). Foley Music [20] proposed an extension tackling this limitation by introducing a Graph-Transformer network to generate MIDI events from human body keypoints and achieved convincing synthesized music from them. Subsequently, Multi-instrumentalist Net [45] extended it further and showed generation of sounds of different instruments in an unsupervised way. Recently, Rhythmic Net [46] demonstrated the possibility to generate music soundtracks synchronized with human movements. In addition to visual cues from human motion, a music Transformer has been proposed to generate video background music [14]. All of these methods use symbolic music representations to train the model and suffer from limited availability of training data in the form of transcribed music paired with videos featuring an instrument playing that music, and thus the generated samples are limited to specific types of instruments and visual scenarios. Compared to the above works, our approach uses in-the-wild music videos to learn a general mapping from visual input to audio waveforms.

## 2.3. Music Generation

It has been shown that using a robust music representation is critical for music generation, and the MIDI representation has been extensively used. Initial works converted MIDI into piano-roll representation using generative adversarial networks [16] or variational autoencoders [41, 22] to generate new music. Later, event-based representations were proposed to represent MIDI more efficiently [38, 25, 23].

Different signals and modalities have been explored to condition the generation of music. For example, Engel *et al.* [17] proposed to constrain generative models to sample for a predefined set of attributes. A Transformer autoencoder has been proposed to aggregate MIDI data across time to obtain a global representation of style from a given performance. Such a global representation can be used to control the style of the music [10]. In [33], a model generating kick drums given conditional signals including beat, downbeat, onset of snare, and bass. Later in [29], event representations were further improved by imposing a metric structure on

input data.

In terms of modeling music on the raw audio level, WaveNet [37] introduced an autoregressive modeling to synthesize music audio with reasonable quality. Later, more efficient methods such as WaveRNN [30] and parallel WaveNet [36] have been proposed to improve the computational complexity. Jukebox [13] applied a hierarchical approach to generate tokens at various temporal resolution which were then combined to reconstruct music. While Jukebox showed high temporal coherence, their audio quality still contains significant artifacts. To tackle both challenges of long-term coherence and high audio quality, more recent works that explored autoregressive models include MusicLM [2], Mubert [35] and AudioGen [32]; while Riffusion [19] and other recent work [27, 34, 28] adopted a diffusion based approach.

Closest to our work would be MusicLM [2]. Two types of discrete tokens are used in the generative framework: 1) semantic tokens that model a long-term structure, extracted from models pretrained on audio data with the objective of masked language modeling, and 2) acoustic tokens provided by a neural audio codec to capture fine acoustic details. No transcripts or symbolic music representations is required. It enables the control of music generation style through text conditioning, and compared the audio generation quality to other text-music system like Mubert [35] and diffusion-based system like Riffusion [19].

## 3. The Proposed Method: V2Meow

In this section, we describe our proposed method, V2Meow, in detail. Starting with feature representations in section 3.1, we describe our modeling pipeline in section 3.2.

### 3.1. Feature Representations

For audio waveforms, we follow the AudioLM [11], using semantic and acoustic tokens extracted from two different pre-trained self-supervised models. For visual inputs, we explore various types of visual features to find the most informative representation suitable for music generation task. Finally, we demonstrate how we represent the control signal without paired music-video-text examples.

**Semantic Music Tokens.** We extract semantic tokens using a pre-trained w2v-BERT model [11]. w2v-BERT is a self-supervised model using masked language modeling (MLM) with contrastive loss, coarsely learning to represent audio, capturing both local dependencies such as local melody in music and global long-term structure such as harmony and rhythm. To obtain the semantic tokens, we first extract embeddings from an intermediate layer of w2v-BERT. We then apply  $k$ -means algorithm with  $K_s$  clusters on these embeddings and use the centroid indices as semantic tokens.

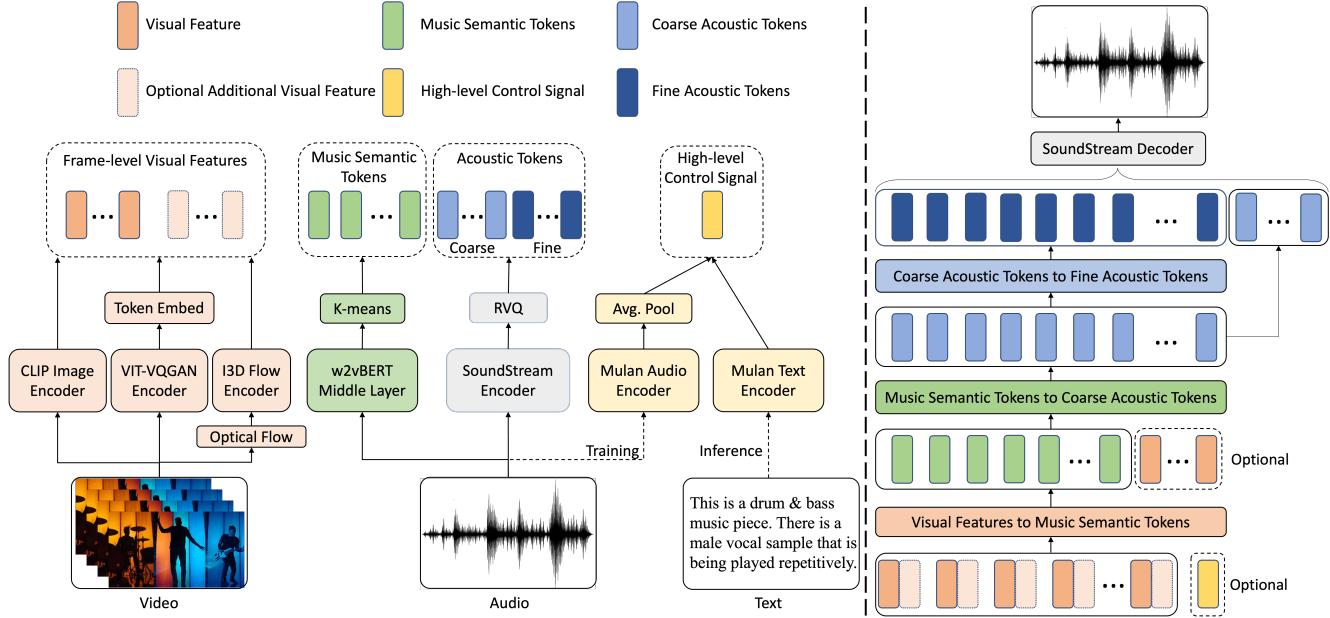


Figure 2: V2Meow Architecture Overview: (left) Feature extraction pipeline for video, audio and text representations. (right) Overview of multi-stage video to music modeling.

For each audio waveform, we obtain semantic tokens  $\{S_t : t = 1, \dots, T_s\}$ , where  $T_s$  is the total number of tokens. While the coarse resolution of the semantic tokens enables us to model long-term dependencies and thus facilitate long-term coherent generation, the audio reconstruction solely from these semantic tokens usually leads to poor quality.

**Acoustic Music Tokens.** To generate high-quality music audio, we additionally rely on acoustic tokens extracted from a pre-trained SoundStream [52] model. SoundStream is a universal neural audio codec that compresses arbitrary audio at low bit rates and reconstructs the audio back in a high quality. Specifically, a convolutional encoder embeds the input waveform, followed by residual vector quantization (RVQ) to discretize them. RVQ is a hierarchical quantization scheme composing a series of  $N$  vector quantizers, where the target signal is reconstructed as the sum of quantizer outputs. Each quantizer with a vocabulary size of  $K_a$  learns to quantize the embedding simultaneously during training. Thanks to the residual quantization, the acoustic tokens have a hierarchical structure such that tokens from the coarse quantizers recover acoustic properties like music recording conditions, while leaving only the fine acoustic details to the fine quantizer tokens. Since coarser levels are more important for high-fidelity reconstruction as illustrated in AudioLM, we follow to first construct a mapping from music semantic tokens to coarse acoustic tokens and then to learn a mapping from coarse acoustic tokens to fine-grained acoustic tokens in the later stage. More details are described in section 3.2.

**Visual Features.** Given a video as a sequence of  $T$  frames,

$\{v_t \in \mathbb{R}^{H \times W \times 3} : t = 1, \dots, T\}$ , we aim to extract useful visual features from existing pre-trained visual model. We explore various visual representations for this, among pure visual models, multimodal models, and quantized models, since it is unclear which kind of visual representation could provide sufficient information for music generation. In particular, we explored a combination of the following visual features as.

1. *Purely visual representations*: Video understanding models learn underlying patterns from the pixel distributions observed in a collection of images or videos, using CNNs [48, 6, 18] or Transformers [3, 4], without access to additional modalities. As it is common that the visual changes in a video have correspondences to musical rhythm, we adopt the Inflated 3D (I3D), which explicitly considers the optical flow, which is known to be useful for analyzing motions. In our experiments, we denote the visual flow embeddings as  $\{f_t \in \mathbb{R}^{D_f} : t = 1, \dots, T\}$ , extracted from an I3D model pretrained on Kinetics [6], where  $D_f$  indicates the dimensionality of the I3D features.

2. *Multimodal embeddings*: The second type is an embedding learned from multimodal correspondence, in addition to the visual modality. Contrastive Language Image pre-training (CLIP) [40] is a popular image-text model, widely used in a variety of downstream tasks including generative applications. We expect its generality and robustness would be potentially useful to incorporate semantics of the video. We denote the CLIP embeddings as  $\{c_t \in \mathbb{R}^{D_c} : t = 1, \dots, T\}$ , where  $D_c$

is the dimensionality of the CLIP embedding.

3. *Visual tokens*: Since the semantic and acoustic music representations in our pipeline are both discrete tokens, we explore using the similar type of discrete tokens for visual inputs. To obtain discrete tokens for a video frame, we adopt ViT-VQGAN [51], the state-of-the-art self-supervised Vision Transformer (ViT) model that performs image quantization on each image to obtain a set of discretized latent codes and uses a Transformer to predict these image tokens autoregressively for image reconstruction. Given a video frame  $\mathbf{v}_t \in \mathbb{R}^{H \times W \times 3}$ , where  $H, W$  indicate the image height and width, respectively, the VIT-VQGAN encodes the image into  $H/D_q \times W/D_q$  discretized latent codes, where  $D_q$  is the size of non-overlapping image patches mapped to one token. A video with  $T$  frames is represented as a set of tokens  $\{Q_t \in \mathbb{Z}_+^{H/D_q \times W/D_q} : t = 1, \dots, T\}$ .

**Control Signal Representations.** Since the music for a video could be highly dependent on personal preference, we allow users to optionally provide a music-related text description, in addition to the visual input, to control the generated music in high-level. However, it is challenging to collect music-video-text pairs in the wild. To overcome this issue, we leverage a music-text joint embedding model, MuLan [26], which is trained on paired music-text data using a contrastive loss. For each video in the training set, V2Meow first extracts MuLan embeddings of all audio segments  $\{\mathbf{m}_j \in \mathbb{R}^{D_m} : j = 1, \dots, J\}$ , where each segment is ten second long and  $J$  indicates the total number of audio segments in the video,  $D_m = 128$  is the dimension of MuLan audio embedding. We then average the embeddings into a single video-level. It is worth noting that we extract a fixed length segment at a random starting point from a music video at each training iteration. Although it would be ideal to perform inference on MuLan with the selected segment only, we avoid doing this aiming for an efficient experiment. Instead, we use a video-level embedding for the entire video and empirically verify that this is sufficient, probably because our goal is to have a high-level control on the style of generated music, instead of fine-grained control. At inference time, we may use a music-related text description to obtain a MuLan embedding and condition our V2Meow model on it.

### 3.2. Modeling Pipeline

We adapt the AudioLM pipeline to train the visual conditioned music generation model. There are three main stages of sequence-to-sequence modeling tasks.

**Stage 1. Visual Features to Music Semantic Tokens.** In the first stage, V2Meow learns a mapping from visual inputs to the music semantic tokens. Specifically, we use an encoder-decoder Transformer [49] where the encoder takes the visual features described in section 3.1, and the decoder

predicts the music semantic tokens autoregressively. It turns out that this stage is the most critical part of generating music which reflects the video well. On the one hand, it builds up the connection between visual and audio modalities, and models the semantic transformation from visual information to audio. On the other hand, this stage does not output high-quality fine-grained audio, allowing the model to focus on associating the two modalities with each other.

**Stage 2. Music Semantic Tokens to Coarse Acoustic Tokens.** In the second stage, we aim to convert the music semantic tokens to acoustic tokens for high-quality synthesis. We follow the AudioLM pipeline to split this stage into coarse and fine acoustic modeling. In the coarse acoustic modeling, we explore two different training strategies: 1) We follow AudioLM to train a decoder-only Transformer to map music semantic tokens to coarse acoustic tokens. Since such a training strategy does not require visual information, we could use the large-scale music data in the wild to pretrain a robust model. 2) We also explore to see whether adding visual conditioning at this stage improves the performance. Specifically, we train an encoder-decoder Transformer model where the encoder takes the visual features and music semantic tokens and the decoder generates the coarse acoustic tokens. While ideally the second approach should work better, the final results are not necessarily better since the amount of music-video pairs available is still incomparable to the amount of music-only data.

**Stage 3. Coarse to Fine Acoustic Tokens and Audio Decoding.** Once we have the coarse acoustic tokens, we follow AudioLM [5] and perform a coarse to fine acoustic tokens modeling. This stage maps the tokens in the first  $N_c$  levels of SoundStream RVQ to the tokens of the remaining  $N_f$  levels. Finally, all levels of tokens are passed to SoundStream Decoder to reconstruct the audio.

**Adding Control.** To incorporate the control signal into V2Meow during training, we simply feed the MuLan audio embedding as an additional input with sequence length be one to the Transformer encoder along with the visual features in the first stage. Both MuLan audio embedding and visual features are projected to the same feature dimension. At inference, we instead use the MuLan text embedding with the visual features to generate the semantic tokens.

## 4. Experiments

### 4.1. Experimental Settings

**Training Datasets.** Following [47], we filtered a public available video dataset [1] to 110k videos with the label Music Videos and refer to it as MV100K. The training and validation datasets were split into an 80:20 ratio. We trained the Stage 1 model and Stage 2 model on these O(100K) music videos and refer to it as MV100K. For audio representations, we adopt the SoundStream tokenizer and w2v-BERT

tokenizer, both of which are pre-trained on the Free Music Archive (FMA) dataset [12].

**Implementation Details.** For all visual features, we use frame rate at 1 fps, following the standard on MV100K [1]. We use the released ViT-L/14 model<sup>1</sup> to extract the CLIP embeddings, whose dimensionality is 768. For computing the I3D Flow embeddings, we use a model pre-trained on the Kinetics dataset, whose dimensionality is 1024. We use a pretrained VIT-VQGAN encoder to obtain 1024 tokens for each image and the vocabulary size is 8192. For visual feature to music semantic tokens modeling, we use encoder-decoder Transformer with 12 layers, 16 attention heads, an embedding dimension of 1024, feed-forward layers of dimensionality 4096, and relative positional embeddings. We use 10-second random crops of the music video for visual to music semantic tokens modeling and semantic tokens to coarse acoustic tokens modeling. The AudioLM coarse to fine acoustic tokens modeling is trained on 3-second crops. During inference, we use temperature sampling for all stages, with temperatures  $\{1.0, 0.95, 0.4\}$  for modelling stages 1, 2, and 3, respectively.

## 4.2. Evaluation

### 4.2.1 Numerical Evaluation

**Evaluation Datasets.** We evaluate our methods on two different datasets. For the task of video conditional music generation, we use the test partition of the MV100K. We select 13 genres of music videos to comprise a genre balanced subset with total number of 4076 videos. More details of the genre balanced subset could be found in the supplementary material. For the task of video and text conditional music generation, we use the latest MusicCaps dataset [2] which is a subset of AudioSet [21]. The MusicCaps has about 5.5k human annotated text caption, music and video pairs. With the text caption, we can verify whether the generated music could be controllable and whether its performance is comparable with text-to-music generation models like MUBERT [35] and Riffusion [19]. For both tasks, we generate ten second audio for each video clip.

**Metrics.** We follow MusicLM [2] to use different quantitative metrics to automatically assess both the fidelity and relevance of the generated samples.

• **Fréchet Audio Distance (FAD)** is used for evaluating the quality of generated audio. The FAD score evaluates the distance between the distribution of synthesized music and distributions of the ground truth music in the test set. To build the distribution, we extract the features before the sound classification layer. It measures audio quality that correlates with human perception. However, it does not evaluate if the generated music matches the music aspects of the original audio. We report the FAD based on two

<sup>1</sup>[huggingface.co/sentence-transformers/clip-ViT-L-14](https://huggingface.co/sentence-transformers/clip-ViT-L-14)

audio embedding models, both of which are publicly available (1) TRILL [43], which is trained on speech data, and (2) VGGish [24], which is trained on the public audio event dataset [1]. Because of the difference in training data, we expect the models to measure different aspects of the audio quality (speech and non-speech, respectively).

- **KL Divergence (KLD)** is used to individually compute the distance between output distributions of synthesized and ground truth features since FAD mainly rely on the distribution of a collection of samples. Instead of measuring the KLD of the waveform, here we adopt a proxy method [50, 32]. We run a LEAF classifier [53] for multi-label classification on AudioSet, and then compute the KL divergence between the predicted class probabilities. Low KLD indicates similar acoustic characteristics. The original audio of the music video is used as reference audio.
- **MuLan Cycle Consistency** In addition to the audio quality metrics, we expect the generated music has consistency with the reference. Therefore, we use the MuLan cycle consistency for this purpose. For the video to music task, we obtain the MuLan audio embedding of both the generated music audio and the ground truth audio, and compute average cosine similarity between the embeddings. For the video and text to music task, we obtain the MuLan audio embedding of the generated music audio and the MuLan text embedding of the text description and compute average cosine similarity between the embeddings.

**Baselines.** For the task of video conditional music generation, since there is no open-source video to music in audio waveform, we compare our V2Meow model against the state-of-the-arts video-driven symbolic music representations-based model [14]. We use the open-source colab inference to generate the audio given the video input. However, since the colab inference only supports uploading one video per inference and generating thousands of examples for quantitative evaluation is infeasible, we only make comparison for the qualitative human perceptual evaluation. To have a quantitative baseline, we randomly shuffle the reference audio and report the sample-based comparison metrics KLD and MCC. For the task of video and text conditional music generation, we compare our approach to two text to music systems Mubert [35] and Riffusion [19]. In Mubert, the text prompt is embedded by a Transformer, music tags which are close to the encoded prompt are selected and used to query the song generation API. Based on the selected tags, Mubert generates a combination of sounds, which in turn were generated by musicians and sound designers. The Riffusion fine-tunes a Stable Diffusion model [42] on mel spectrograms of music pieces from a paired music-text dataset.

**Quantitative Results.** Quantitative evaluation results are shown in Table 1. For MV100K, we observe that adding visual input at the acoustic modeling stage significantly improves both audio quality related metrics and MuLan cosine

Method	Visual	Text	Semantic / Semantic + Acoustic Modeling			
			FAD TRILL ↓	FAD VGG ↓	KL Div. ↓	MCC ↑
<b><i>Eval Dataset: MV100K</i></b>						
Random Shuffle	✗	✗	-	-	0.67	0.268
V2Meow Clip emb	✓	✗	0.236/0.158	6.094/2.779	0.63/0.54	0.312/0.372
V2Meow I3D Flow emb	✓	✗	0.236/ <b>0.151</b>	6.278/2.328	0.77/0.65	0.279/0.296
V2Meow VIT-VQGAN tokens	✓	✗	0.240/0.174	6.097/1.988	0.73/0.62	0.276/0.294
V2Meow VIT-VQGAN tokens + I3D Flow emb	✓	✗	0.236/0.178	5.801/ <b>1.945</b>	0.68/0.57	0.298/0.327
V2Meow Clip + I3D Flow emb	✓	✗	0.235/0.165	6.126/2.003	0.64/ <b>0.49</b>	0.343/ <b>0.419</b>
<b><i>Eval Dataset: MusicCaps</i></b>						
Riffusion [19]	✗	✓	0.760	13.4	1.19	0.34
MUBERT [35]	✗	✓	0.450	9.6	1.58	0.32
V2Meow Clip emb	✓	✓	0.379/ <b>0.328</b>	5.198/4.628	1.31/1.19	0.364/0.377
V2Meow I3D Flow emb	✓	✓	0.389/0.331	5.190/ <b>4.623</b>	1.26/1.22	0.377/0.371
V2Meow VIT-VQGAN tokens	✓	✓	0.377/0.366	4.970/5.039	1.34/1.23	0.380/0.392
V2Meow VIT-VQGAN tokens + I3D Flow emb	✓	✓	0.381/0.359	5.094/4.819	1.34/1.21	0.379/0.389
V2Meow Clip + I3D Flow emb	✓	✓	0.391/0.349	5.385/4.948	1.27/ <b>1.19</b>	0.369/ <b>0.394</b>

Table 1: Quantitative evaluations on MV100K and MusicCaps for different models. For FAD and KL Divergence, lower is better. For MCC, higher is better. Bold font indicates the best value.

similarity between generated and reference music by a largin margin. We further observe that as a single visual input, clip embedding achieves the best MCC score while I3D flow embedding results in better performance at FAD metrics. This indicates that each type of visual input could be beneficial to certain types of aspects. Indeed, the combination of Clip and I3D Flow embedding achieves the best MCC score across all models and also the FAD VGGish is boosted from the model with either Clip or I3D Flow embedding. While the VIT-VQGAN tokens do not outperform others in any metric, we still find the combination of VIT-VQGAN tokens and I3D Flow embedding achieves better performance than single visual input. For MusicCaps evaluation, our approach outperforms Riffusion and MUBERT in both audio qualty metrics and MuLan Cycle consistency. It is worth to note that while our V2Meow model only use video-level MuLan embedding and trained on a O(100K) music videos, we still achieve better numerical performances than pure text-to-music generative model. In terms of visual input modalities, we observe that the combination of Clip and I3D Flow embeddings reaches the best MCC score again while the music quality is slightly worse than the single modality.

#### 4.2.2 Human Study

Whether video and background music match is subjective. The generated music can be a reasonable match to the video, even if it is not similar to the ground truth music that accompanies the original video. Thus we cannot only rely on distance metrics between the generated and ground truth music to measure the visual-music correspondence, we have to rely on human study.

For the human study, we specifically sampled 89 distinct

video examples from the MV100K test set and 76 distinct video examples from the MusicCaps test set, both of which were used in the numerical evaluation. For each video input we requested human raters to conduct a side-by-side comparison of the music generated from the baseline models (CMT, Riffusion, or MUBERT) and the five different V2Meow model variants. For all surveys, no background on the survey or our approach was given to the participants to avoid perceptual biases. We surveyed around 200 participants individually, where each participant was asked to evaluate a pair of videos with same video but different background music (See Appendix C for details). Each video pair is rated by 3 person. A total number of 3500 ratings are collected in the end. The design mostly follows [54] but with some modifications:

- **Visual Relevance.** This task evaluates audiovisual correspondence between the video-conditioned generated music and the reference music in terms of 1) Semantic correspondence which demonstrates the correctness of the generated music, whether it matches the visual semantic content, and 2) Temporal correspondence: If temporally synchronized with the video. We asked people to watch the same video with two different synthesized music and answer the question: "Which music do you think goes best with the video?". They are asked to ignore the sound quality and only focus on how well the music matches the video.

- **Music Preference.** This task subjectively evaluates whether the generated music has desired music traits from the human perspective, e.g., whether it contains irritating noise, weird chords, sudden silence, awkward usage of instrument. We asked people (non-expert) to choose which music they prefer to hear and ignore the video content. This task aim to study whether the generated music is aligned

Model\Metrics	Visual	Text	Visual Relevance	Music Preference
<i>Eval Dataset: MV100K</i>				
CMT [14]	✓	✗	20.6%	30.0%
Riffusion [19]	✓	✗	N/A	N/A
MUBERT [35]	✓	✗	N/A	N/A
V2Meow CLIP embs	✓	✗	78.2%	67.6%
V2Meow I3D Flow embs	✓	✗	74.3%	65.8%
V2Meow VIT-VQGAN tokens	✓	✗	81.4%	71.5%
V2Meow CLIP+I3D Flow embs	✓	✗	79.2%	68.2%
V2Meow VIT-VQGAN tokens+I3D Flow embs	✓	✗	83.8%	76.8%
<i>Eval Dataset: MusicCaps</i>				
CMT [14]	✓	✗	19.7%	20.7%
Riffusion [19]	✓	✓	38.6%	41.2%
MUBERT [35]	✓	✓	43.3%	49.3%
V2Meow CLIP embs	✓	✓	63.6%	58.5%
V2Meow I3D Flow embs	✓	✓	68.8%	68.0%
V2Meow VIT-VQGAN tokens	✓	✓	66.9%	60.3%
V2Meow CLIP+I3D Flow embs	✓	✓	67.4%	65.8%
V2Meow VIT-VQGAN tokens+I3D Flow embs	✓	✓	71.8%	67.1%

Table 2: Human perceptual evaluation on matching and quality metrics. The value indicates the percentage of people who select the method. All the video-to-music model variants are compared with CMT as baseline for the MV100K evaluation in a pair-wise human study. All the video-text-to-music variants are compared with the Riffusion and MUBERT for the MusicCaps evaluation.

with human perceptual preference. As the audio quality is better judged by the FAD metric, here we ask the listener to ignore sound quality and tell us which music they like.

**Qualitative Results.** We evaluate both listening tasks for two genre-balanced subset sampled from MV100K and the MusicCaps [2] used for our numerical evaluation described in section 4.2.1. From results shown in Table. 2 (left column), we observe a clear indication that the music clips generated with the proposed models are rated as the best match to the visual content more frequently compared to the MIDI-based video-to-music generation baseline CMT [14]. In terms of music preference, as our approaches can generate music with finer details and complex pattern, they are also preferred compared to MIDI baseline, which tends to generate simpler music patterns. The results shown on the right column in Table. 2 suggest that compared to text-to-music generation models like MUBERT and Riffusion, our generated music is more aligned with the video content, a result of additional video conditioning. In the supplementary material, we sampled a genre balanced subset from the human study and present the side-by-side comparison.

### 4.3. Ablation Studies

We performed ablation studies to answer the following questions. **Q1:** What is the contribution of each model component to the audio quality for video conditional music generation task? **Q2:** What is the contribution of each model component to the music and text consistency for video and text conditional music generation task? **Q3:** How does the component of V2Meow influence the perception of the gen-

erated music? For all studies, we fix the visual input to be the clip embedding and only change the model components.

**Q1.** We perform experiments to understand the contribution of each component for audio quality. Results of FAD VG-Gish scores are shown in Fig. 3(a). We first observe that without acoustic modeling, we could not generate faithful music audio waveforms. With acoustic modeling, the audio quality gets improved significantly. With the stages of semantic modeling and coarse to fine acoustic modeling, our full model achieves high fidelity audio in the end.

**Q2.** For visual and text conditional music generation, we use the cosine similarity of MuLan embedding of text caption and MuLan embedding of generated audio to demonstrate contribution of each component. The results are shown in Fig. 3(b). We first verify that MuLan can boost the consistency between text caption and generated music. Furthermore, we show that the acoustic modeling stage is also critical for achieving higher MuLan cycle consistency.

**Q3.** In an additional human evaluation survey, we performed a perceptual ablation study to test how the component in V2Meow pipeline influences the perception of the generated music compared to the approaches without it. Survey results shown in Table 3 suggest that adding additional I3D Flow features to the CLIP-based model variant appears to improve the quality of the generated music. However, when combined with VIT-VQGAN tokens, the music quality is perceived to have decreased. Detailed per genre analysis can be found in Appendix D.

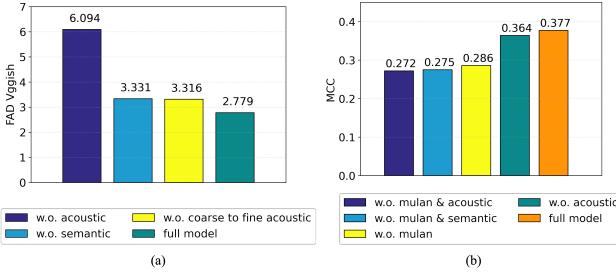


Figure 3: (a) Ablation study on the contribution of each component for MV100K dataset using FAD VGGish score, the lower the better. (b) Ablation study on the contribution of each component of for MusicCaps dataset using MuLan and Text consistency, the higher the better.

Base Model\Component	Visual Relevance	Music Preference
CLIP	47.2%	49.0%
CLIP + I3D Flow	63.0%	61.8%
VIT-VQGAN	55.9%	53.6%
I3D Flow	41.7%	40.7%
VIT-VQGAN + I3D Flow	42.6%	45.3%

Table 3: Ablation study on human perceptual evaluation. The value indicates the percentage of people who select the method. The statistics is compute from around 1409 ratings.

## 5. Conclusion

We present V2Meow, a video conditional music generative model. Our model can effectively generate high-fidelity music from silent video input by relying on the video’s semantic and temporal context. We achieve such function by leveraging multi-stage semantic and coarse to fine acoustic visual to music modeling inspired by MusicLM. To evaluate the music-video correspondence between the video and the generated music, we have established both subjective and objective evaluation metrics to measure the quality of the generative music. Experimental results demonstrate that compared to MIDI-based generation models, V2Meow can generate music that is more aligned with the visual content and human perception. Further, the human study has shown that compared to text-to-music generation model, additional video input results in higher music-video correspondence. Ablation studies have demonstrated all components are critical for generating high-fidelity sounds from video inputs, and how the choice of different video features affects the generation quality.

## 6. Broader Impact

Controllable generative models such as V2Meow can serve as the foundation for new tools, technologies, and practices for content creators. While our motivation is to support creators to enrich their creative pursuits, we acknowledge

that these models need to be developed and deployed in a manner that takes into account the values and wellbeing of creators, their communities, and society.

In particular, large generative models learn to imitate patterns and biases inherent in the training sets, and in our case, the model can propagate the potential biases built in the video and music corpora used to train our models. Such biases can be hard to detect as they manifest in often subtle, unpredictable ways, which are not fully captured by our current evaluation benchmarks. Demeaning or other harmful language may be generated in model outputs, due to learned associations or by chance. A thorough analysis of our training dataset shows that the genre distribution is skewed towards a few genres, and within each genre, gender, age or ethical groups are not represented equally. For example, male is dominant in hip-hop and heavy metal genre. These concerns extend to learned visual-audio associations, which may lead to stereotypical associations between video content (i.e. people, body movements/dance styles, locations, objects) and a narrow set of musical genres; or to demeaning associations between choreography in video content and audio output (i.e. minstrelsy, parody, miming). ML fairness testing is required to understand the likelihood of these patterns in any given model and effectively intervene in them. We expand on these concerns in our data and model card.

As such, in tandem with our algorithmic advances, we are actively working both internally and externally on initiatives to support the understanding and mitigation of possible risks of bias inherited from the training data, cultural appropriation and stereotyping, and erasure of cultural and political context of music. Further work is required to make determinations about whether the audio generated is contextually appropriate, which extends beyond technical measurements, or tempo or rhythmic alignment. This requires understanding of social and musical context, and is best done in collaboration with cultural and musical experts. We stress that these issues and others are as important and valuable as algorithmic advances that sometimes overshadow the broader context in which models exist.

## 7. Acknowledgements

We are grateful for having the support from Jesse Engel, Ian Simon, Hexiang Hu, Christian Frank, Neil Zeghidour, Andrea Agostinelli, David Ross and authors of MusicLM project for sharing their research insights, tutorials and demos. Many thanks to Austin Tarango, Leo Lipsztein, Fernando Diaz, Renee Shelby, Rida Qadri and Cherish Molezion for reviewing the paper and supplementary materials and share valuable feedbacks regarding responsible AI practice. Thanks Sarvejet Singh, John Anderson, Hugo Larochelle, Blake Cunningham, Jessica Colnago for supporting publication process. We owe thanks to Muqthar Mohammad, Rama

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## A. Video Examples

Here we showcase the diverse range of video input types supported by V2Meow models<sup>2</sup>. We demonstrate this with highly rated examples from MV100K and MusicCaps in Figure 4, which offer videos with both music-related and non-music-related scenes. We classify a scene as music-related if it contains a source of music, such as musical instruments like drums and guitar, live performances, or people singing. Scenes without these elements are not directly related to music, such as video logs of skateboarding, friends hanging out in a camping trip, dance videos, and slide shows of landscape photos. Compared to MV100K, MusicCaps features more dance videos, videos with statics images, or lyric videos, which are sampled from AudioSet<sup>3</sup>.

Our human study results suggest that V2Meow can handle a wide range of video input types and generate visually relevant soundtracks. For music-related scenes, human raters consider the generated music aligned with the video semantic if it features the sound of the instrument, aligns with the music genre indicated by the combination of these instruments, or features vocals that accompany the movement of facial features. The audio-visual correspondence is abstract rather than physical. The generated music does not need to rigorously follow the exact melody the artist was playing or reproduce precisely what was said or sung to be considered as visually relevant. For non-music-related scenes, if the generated music matches the mood and temporal changes in the scene, it is deemed visually relevant.

In addition, we evaluate V2Meow’s performance on out-of-domain video input types, such as cat videos. Figure 5 shows three examples of generated music audios from a 10-second cat video clip. The first piece of music is a fast-paced happy song with 140 bpm. The second piece of music features a transition from a calming tune to an upbeat energetic tune, which matches the audio event at  $t=7s$  when the cat starts to eat. The third piece is an acoustic guitar solo. The generated music can be controlled via a text prompt as shown in Figure 6. By altering the text prompts, we can add additional control of the generated music on genre, mood, etc., while still being aligned with the video input. For example, with the text prompt “Drum and Bass” we can break

<sup>2</sup>listening examples will be available at <https://google-research.github.io/v2meow>

<sup>3</sup>[https://research.google.com/audioset/ontology/music\\_1.html](https://research.google.com/audioset/ontology/music_1.html)

the undesirable association between the cat video and hard rock music, and generate a soundtrack with dancing beats.

## B. Data Details

### B.1. MV100K

For training data we leverage the 100K music videos [47] referred here as MV100K. To understand the genre distribution of our training data, we’ve trained an AudioSet classifier to label the genres of the validation set of size around 22K videos. The multi-label classifier is trained on the music portion of AudioSet data, with a AUC-ROC score of 0.936 on the validation split.

As shown in Figure 7, the majority of samples are Pop, Hip-hop and Rock, which is similar to the genre statistics reported by [47] on the same MV100K dataset but different in orders. As the train split and validation split share the same distribution, we can conclude that the genre distribution of the training split of MV100K is also skewed and unbalanced. We refer reader to [47] for detailed analysis of gender vs genre, race vs genre, age vs genre, visual scene vs genre and instrument vs genre in the training data. For example, per genre analysis has shown that for genre like heavy metal, hard rock, hip hop, it’s predominantly male, which may establish a stereotypical relationship between the gender presented in the video input and genre of the generated music. Text-based high-level control can be of great help to handle such bias inherited from the training data.

For numerical evaluation, we selected 4550 genre-balanced 10-seconds video clips from the MV100K validation split. The genre distribution can be found in Table 4. For human study we further sub-sampled 89 distinct examples from 9 different genres. Note that “Rock” genre in AudioSet is a parent genre for Punk rock and Heavy metal. In this study, Rock genre represents all music clips that are not Punk rock or Heavy metal.

### B.2. MusicCaps

MusicCaps is a music caption dataset derived from AudioSet, where it contains 5,521 audio clips with detailed description of the music audio. Here we augment the dataset with 10-s video clip. The genre distribution can be found in [2]. For human study, we sampled 100 genre-balanced examples from the MusicCaps.

## C. Human Study Details

As shown in Figure 8, around 200 participants in the listening test were presented with two 10-second clips that have different background music, and asked to compare two background music in terms of 1) visual relevance 2) music preference on a 5-point Likert scale. We refer readers to section 4.2 for the task details. Each pair of radio is

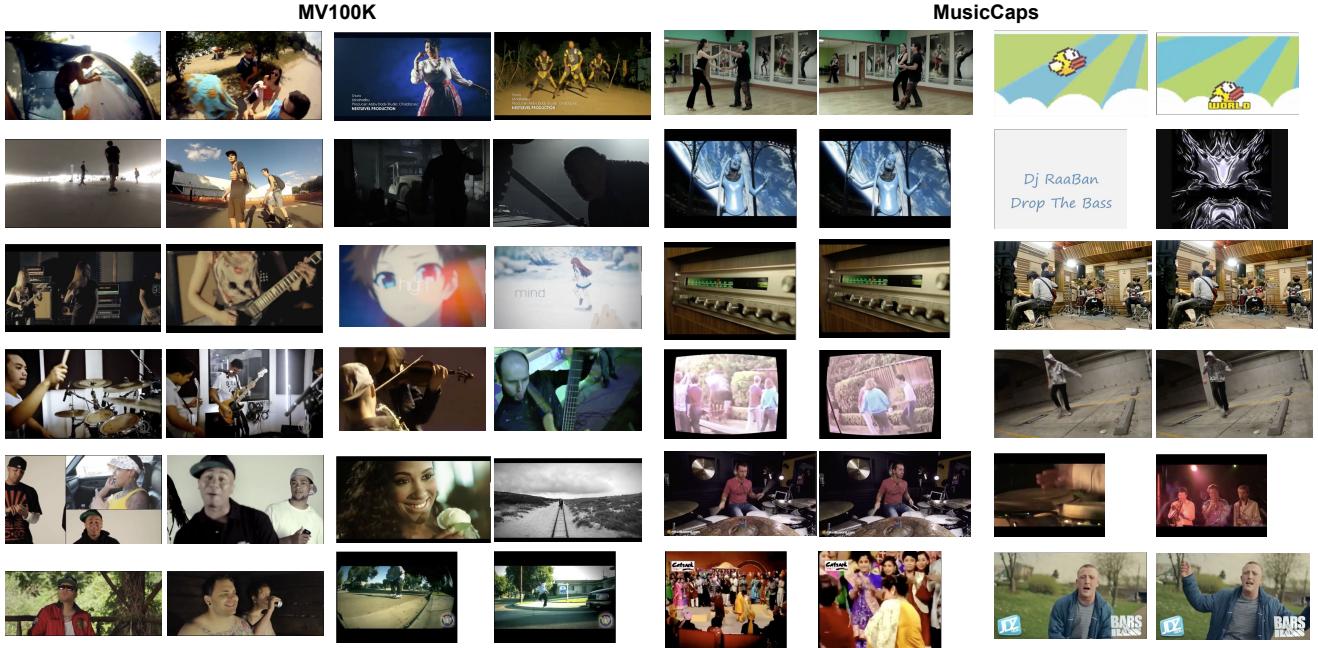


Figure 4: Videos Included in Human Study: (left) Example video inputs included in the MV100K test set. (right) Example video inputs included in the MusicCaps test set. Two frames are shown for each video.

Genre Mid	Genre Name	No. of Examples	In Human Study
/m/02lkt	Electronic\music	350	YES
/m/0glt670	Hip\hop\music	350	YES
/m/064t9	Pop\music	350	YES
/m/05r6t	Punk\rock	350	YES
/m/05rwpb	Independent\music	350	NO
/m/06j6l	Rhythm\and\blues	350	NO
/m/03lty	Heavy\metal	350	YES
/m/028sqc	Music\of\Asia	350	YES
/m/06cqf	Reggae	350	YES
/m/02mscn	Christian\music	350	NO
/m/0g293	Music\of\Latin\America	350	NO
/m/0164x2	Music\of\Africa	350	YES
/m/06by7	Rock	350	YES

Table 4: Genre distributions of MV100K used in numerical study.

rated by 3 raters. The order of the video clips shown to the listeners is randomized to prevent biased ratings.

For the experiment shown in the left column of Table 2, we compare each of the 5 video-to-music variants with baseline model CMT on 89 distinct video examples from MV100K, and collected 1424 ratings. The detailed pairwise comparison between V2Meow models and CMT can be found in Figure 10.

For the experiment shown in the right column in Table 2, we compare each of the 5 video-text-to-music variants with baseline model CMT, mubert and riffusion on 76 distinct

video examples from the MusicCaps dataset. For each pair of models, we sample 50 examples randomly. As each example is rated by 3 raters, in the end we've collected 2392 ratings. The detailed pairwise comparison results for visual relevance is shown in Figure 11 and results for music quality is shown in Figure 12.

## D. Ablation Study and Genre Analysis

We've also run ablation study on MV100K to compare different visual features and their impacts on visual relevance and music quality. For each genre and each pair of

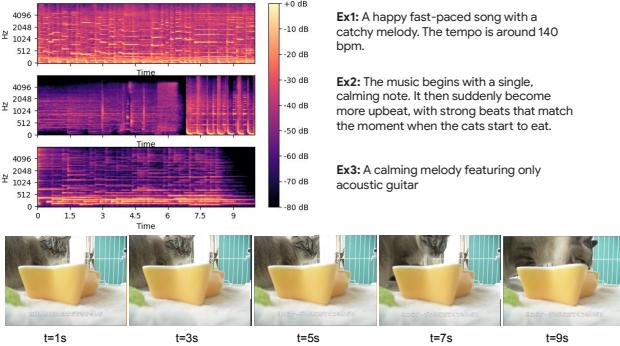


Figure 5: Out-of-Domain Example Analysis: Here we show melspectrograms of 3 music audios generated from the same cat video clip, which features an out-of-domain object, i.e., cat and an audio event, i.e., cat starts to eat at  $t=7s$ .

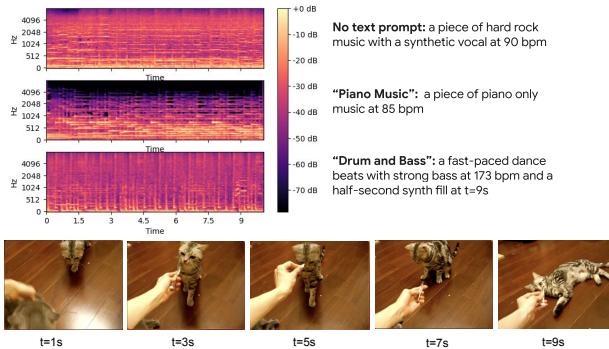


Figure 6: Out-of-Domain Example with Text Control: Here we show melspectrograms of 3 music audios generated from the same cat video clip, with an optional text prompt for control.

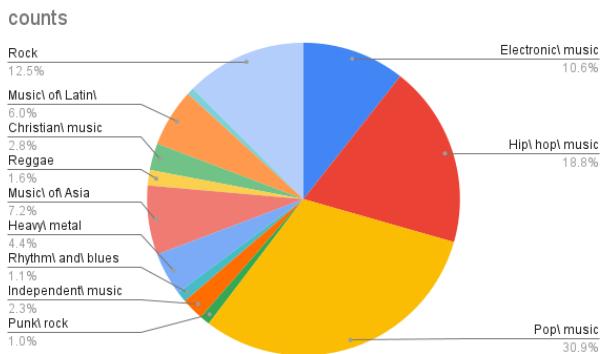


Figure 7: Genre distribution of MV100K.

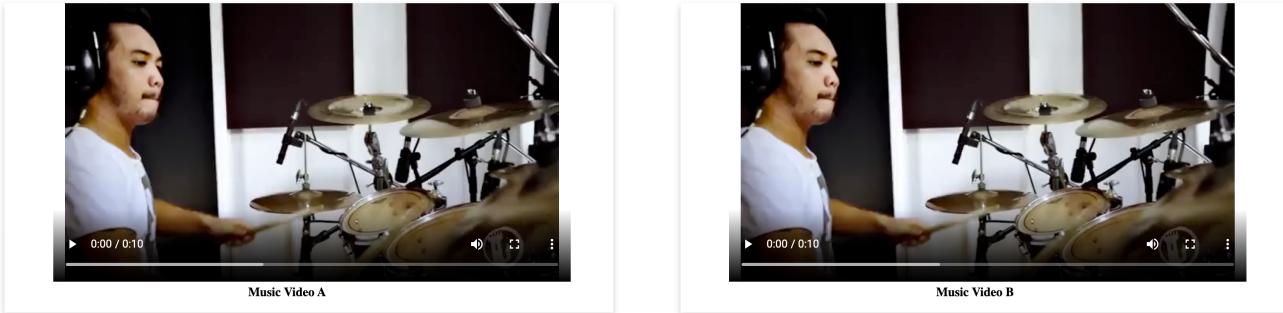
video-to-music model variants (a total of 10 pairwise combination were made from the 5 available model variants), we randomly sample 5 examples resulting in 50 pairs of generated soundtrack per genre and around 150 ratings per

genre for pairwise comparison. The total number of pairwise ratings is 1409. The winning rate per genre is calculated as the ratio of the number of Strong or Weak Preference out of 150 ratings. The average winning rate is the winning rate per genre averaged over 9 genres.

As shown in Table 3, Clip+flow and ViT model have been the top 2 preferred model if measured by the average winning rate for both the visual relevance and music quality task. As shown in the per genre analysis in Figure 9, Clip+Flow model is also the best performing model for most genres especially Music of Asia, a genre features predominantly dance videos like KPop videos. While ViT model performs best for Reggae. For most genres, the combination of Clip and Flow results in better performance, as Clip tends to capture semantic context and Flow tends to capture temporal context. However, in the Punk Rock genre Clip model performs better than the Clip+Flow model, which can be explained by the stronger connection between the semantic context of the video and the Punk Rock genre and weaker connection between the temporal context.

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**Q1 : Which music do you think goes best with the video?**

Note: Please ignore audio quality and just focus on how well the background music matches the video

A :

- Strong preference for A
- Weak preference for A
- No preference
- Weak preference for B
- Strong preference for B

**Q2 : Which background music do you prefer to hear?**

Note: Please ignore audio quality and video content, just focus on the musical properties when deciding which music you like

A :

- Strong preference for A
- Weak preference for A
- No preference
- Weak preference for B
- Strong preference for B

SUBMIT

Figure 8: The UI for Human Study.

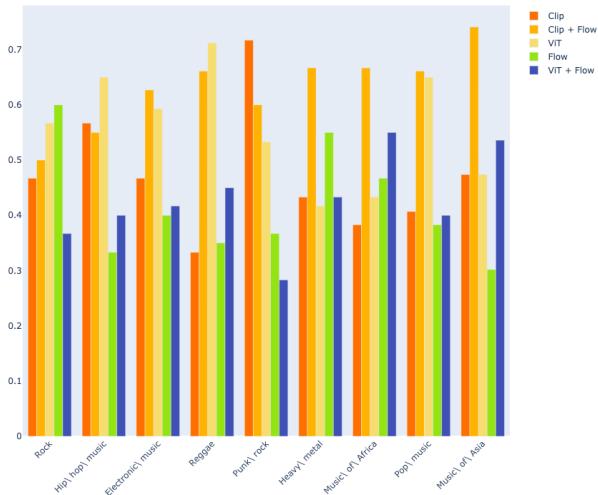


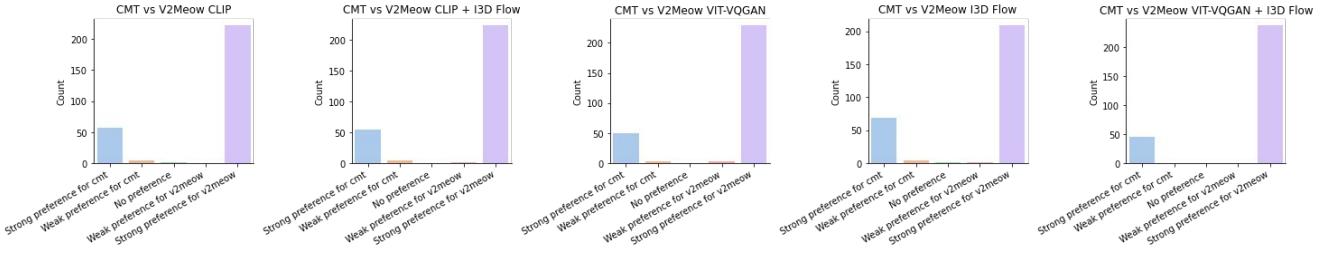
Figure 9: Model winning rate per genre for visual relevance task.

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## Visual Relevance



## Music Preference

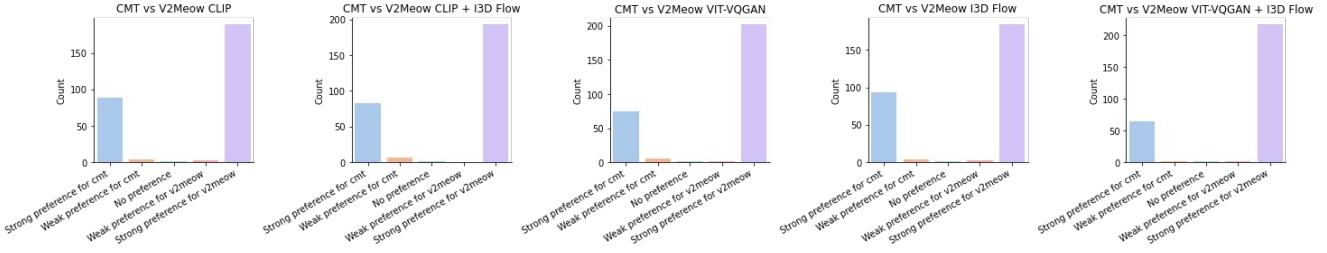


Figure 10: Pairwise comparisons of visual relevance and music preference from the human listener study on MV100K. Each pair is compared on a 5-point Likert scale.

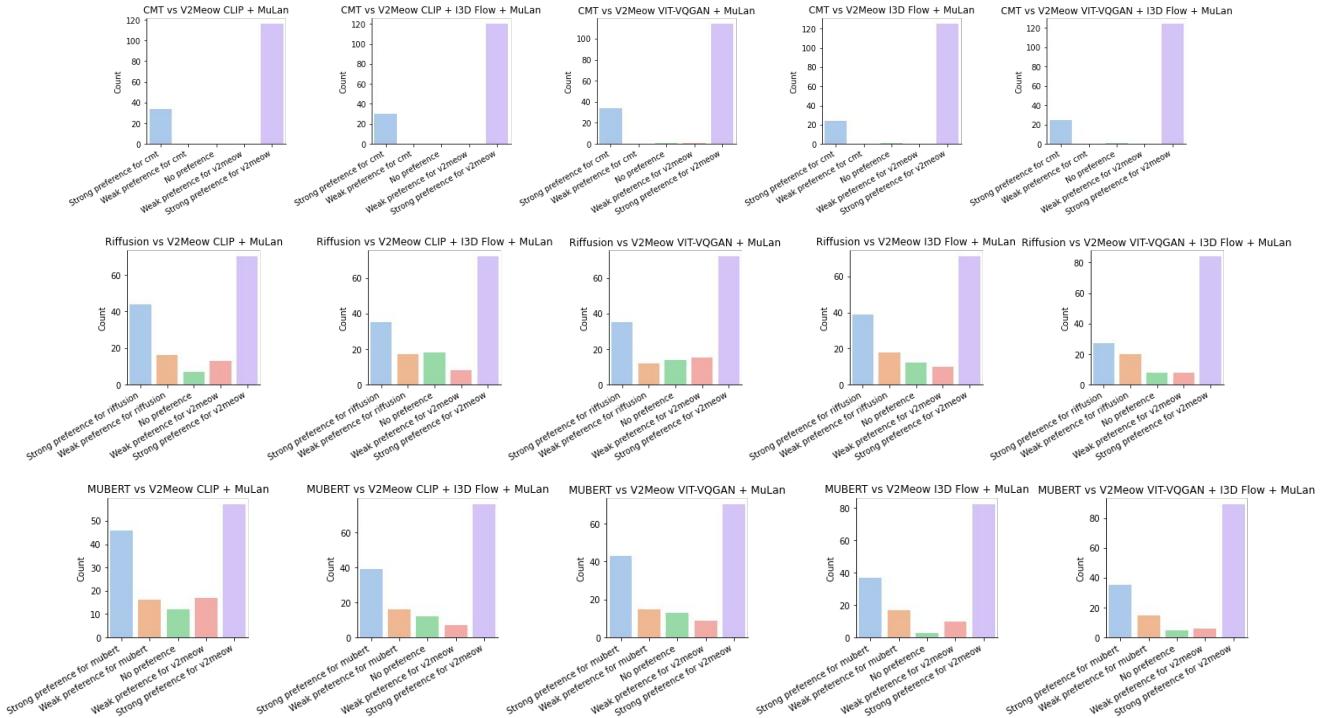


Figure 11: Pairwise comparisons of visual relevance from the human listener study on MusicCaps. Each pair is compared on a 5-point Likert scale.

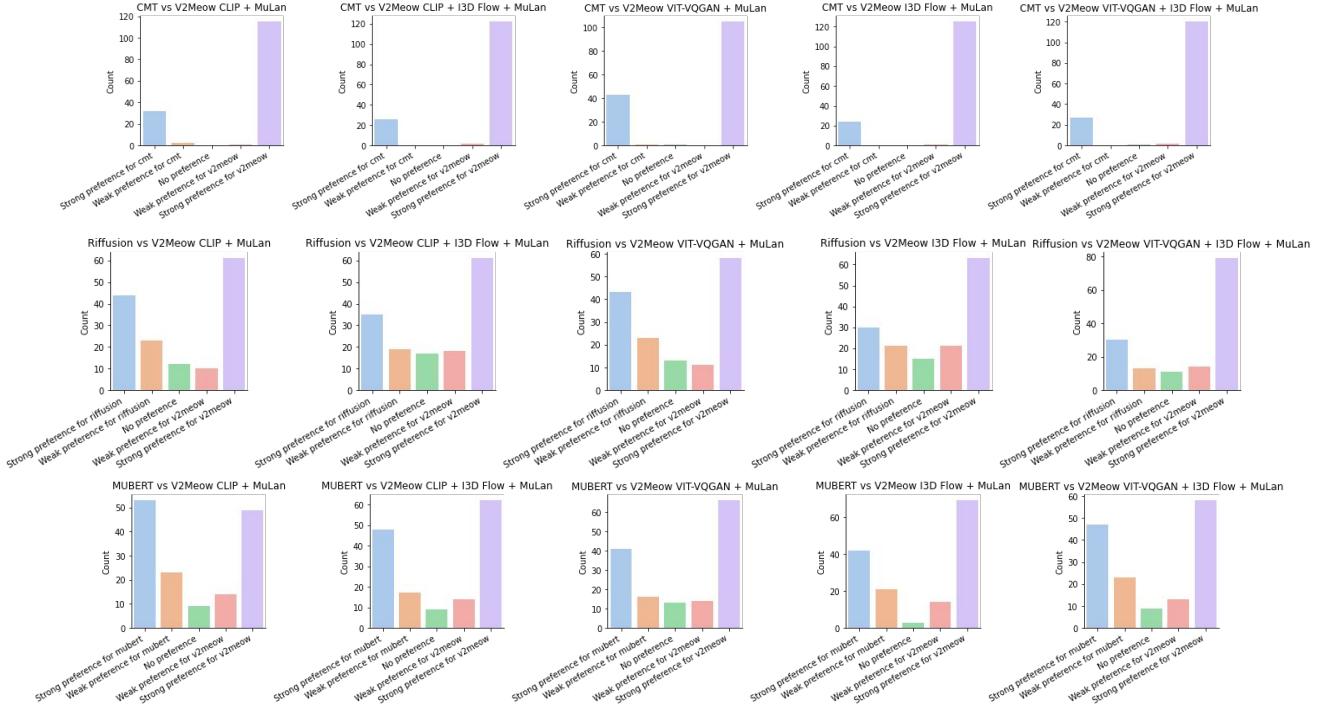


Figure 12: Pairwise comparisons of music preference from the human listener study on MusicCaps. Each pair is compared on a 5-point Likert scale.

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