# COCOLA: Coherence-Oriented Contrastive Learning of Musical Audio Representations

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Abstract—We present COCOLA (Coherence-Oriented Contrastive Learning for Audio), a contrastive learning method for musical audio representations that captures the harmonic and rhythmic coherence between samples. Our method operates at the level of the stems composing music tracks and can input features obtained via Harmonic-Percussive Separation (HPS). COCOLA allows the objective evaluation of generative models for music accompaniment generation, which are difficult to benchmark with established metrics. In this regard, we evaluate recent music accompaniment generation models, demonstrating the effectiveness of the proposed method. We release the model checkpoints trained on public datasets containing separate stems (MUSDB18-HQ, MoisesDB, Slakh2100, and CocoChorales).

Index Terms—Contrastive learning, generative AI, music information retrieval, performance evaluation

## I. INTRODUCTION

Recently, there have been significant advances in music generation in the continuous domain [1]-[4], thanks to the impressive development of generative models [5], [6]. In addition to producing high-quality tracks of increasing length [3], these models offer precise semantic control through textual conditioning [7], [8]. However, they are limited as tools for musical composition, since they output a final mix containing all stems. To overcome this, a new range of compositional generative models for music is emerging [9]-[11], where (i) the generative tasks are defined at the stem level and (ii) their usage is iterative/interactive. The most important application of these models is accompaniment generation, where, given multiple conditioning sources, the model is asked to output a *coherent* stem that should combine with them in a harmonically and rhythmically consistent way, as opposed to being dissonant. While pioneering models [12], [13] could generate waveform accompaniments, their output is limited to a single stem category, and as such they cannot be used iteratively (acting sequentially on the model's outputs) in a composition process.

A significant problem with this line of research is the lack of an objective metric for quantifying the coherence of the

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Fig. 1. **Illustration of COCOLA Score.** COCOLA is a contrastive model that estimates the coherence between instrumental tracks and generated accompaniments.

generated outputs w.r.t. the inputs. For example, [9] proposes the sub-FAD metric as a multi-stem generalization of the FAD [14] protocol proposed in [13]. However, this metric is not optimal for assessing coherence, as it focuses on global quality instead of the level of harmony and rhythm shared by constituent stems. To this end, we propose and release<sup>1</sup> a novel contrastive model called COCOLA (Coherence-Oriented Contrastive Learning for Audio), which can evaluate the coherence between conditioning tracks and generated accompaniments (Figure 1). The model is trained by maximizing the agreement between disjoint sub-components of an audio window (submixtures of stems) and minimizing it on sub-components belonging to different windows. With the model, we define a COCOLA Score as the similarity between conditioning tracks and accompaniments in the embedding space, which we use to evaluate accompaniment generation models.

After discussing related work in Section II, we introduce COCOLA in Section III. We describe the experimental setup in Section IV and present the results in Section V. We conclude the article in Section VI.

<sup>1</sup>https://github.com/gladia-research-group/cocola



Fig. 2. The COCOLA training procedure (single stem case). We first randomly crop windows of size L from a batch of K tracks (depicted on the left). As a second step, we randomly select two distinct stems in each window. For example, in the first window, we select  $\mathbf{x}_1^1$  (Guitar) and  $\mathbf{x}_3^1$ (Drums). Thus, we embed all selected stems with the COCOLA encoder  $f_{\theta}$ , obtaining latent representations. For example, we obtain  $\mathbf{h}_1^1$  and  $\mathbf{h}_2^1$  from the first window. Finally, we compute the contrastive loss (Eq. (3)) considering embeddings belonging to the same window as positive pairs and combinations of embeddings between different windows as negative pairs.

# II. RELATED WORK

## A. Contrastive Methods for Audio

Contrastive learning [15], [16] can be formulated both as a supervised or self-supervised problem.

Supervised contrastive learning methods often rely on crossmodal approaches, requiring labeled data alongside audio. Early works [17] employ the contrastive loss [18] for aligning audio with simple labels. MuLaP [19] was the first model to jointly represent audio and complex text using a joint transformer encoder with cross-attention layers. Recent models [7], [20], [21] have adopted separate text and audio encoders, allowing independent use of these branches during inference.

Self-supervised representation learning methods [22], [23] create embeddings from structural information in audio data. In [24], positive examples for triplet loss are built using Gaussian noise, time/frequency translations, and time proximity, without ensuring coherence (e.g., mixing unrelated sounds). Following methods [25] adapted the contrastive loss. COLA [26] uses the simple criterion of sampling positive pairs only from the same audio track, outperforming a supervised baseline. [27] pairs mixtures with sources extracted via source separation.

The proposed COCOLA method combines elements of both supervised and self-supervised approaches. Since stems are pre-separated, it is not fully self-supervised, but like self-supervised methods, it processes data using a uni-modal encoder.

## B. Waveform Music Accompaniment Generation Models

MSDM [9], based on diffusion models [5], [6] was the first model able to generate waveform accompaniments belonging to different stem classes. Following, state-of-the-art models [11], [28] took the form of conditional generative models which respond with an output stem to an input track. Based on generative source separation via Bayesian inference [29]–[31], GMSDI [32] performs the tasks of MSDM, requiring models trained only with mixtures and text, by separating sources while generating them.

Another category of models [10], [33], following AUDIT [34], perform music editing by modifying the input track. Such models can add instruments to a track, but given the generative nature of the model, isolating such stems via difference with the input or source separation can introduce artefacts.

#### III. METHOD

# A. Stem-Level Contrastive Learning

In our setting, we have access to a dataset  $D = \{\bar{\mathbf{x}}^k\}_{k=1,...,\bar{K}}$  containing  $\bar{K}$  musical tracks  $\bar{\mathbf{x}}^k$ , each separated into a variable number N of individual stems  $\bar{\mathbf{x}}^k_n$ , i.e.,  $\bar{\mathbf{x}}^k = \{\bar{\mathbf{x}}^k_n\}_{n=1,...,N}$ . As a first step, we sample a batch of  $K < \bar{K}$  tracks  $\{\bar{\mathbf{x}}^k\}_{k=1,...,K}$  from D, with possible repetitions. Following, we slice a window  $\mathbf{x}^k$  of size L for each track  $\bar{\mathbf{x}}^k$  in the batch (all stems in a window share the same length), such that no window contained in the same track overlaps for more than a ratio r, obtaining a new batch  $\{\mathbf{x}^k\}_{k=1,...,K}$ . Afterward, we select, for each k, two disjoint non-empty stem subsets  $X_1^k, X_2^k$  of  $\mathbf{x}^k$ . We define the submixes  $\mathbf{m}_1^k$  and  $\mathbf{m}_2^k$  by summing the stems in  $X_1^k, X_2^k$ :

$$\mathbf{m}_1^k = \sum_{\mathbf{x}_n^k \in X_1^k} \mathbf{x}_n^k, \qquad \mathbf{m}_2^k = \sum_{\mathbf{x}_n^k \in X_2^k} \mathbf{x}_n^k.$$
(1)

When  $X_1^k, X_2^k$  are singletons, the sub-mixes are simply two stems in the window (single stem case).

Like in COLA [26], we use a convolutional audio-only encoder<sup>2</sup>  $f_{\theta} : \mathbb{R}^{L} \to \mathbb{R}^{d}$ , mapping  $\mathbf{m}_{1}^{k}$  and  $\mathbf{m}_{2}^{k}$  to lowerdimensional embedding vectors  $\mathbf{h}_{1}^{k} = f_{\theta}(\mathbf{m}_{1}^{k})$  and  $\mathbf{h}_{2}^{k} = f_{\theta}(\mathbf{m}_{2}^{k})$ , with d the embedding dimension. The COCOLA training procedure maximizes the agreement between pairs  $\mathbf{h}_{1}^{k}, \mathbf{h}_{2}^{k}$  of sub-mixes embeddings in the same window. It decreases it for pairs  $\mathbf{h}_{1}^{k}, \mathbf{h}_{2}^{j}$  ( $j \neq k$ ) of sub-mixes embeddings in different windows. As in COLA, we use a bilinear similarity metric:

$$\operatorname{sim}(\mathbf{h}_1^k, \mathbf{h}_2^j) = (\mathbf{h}_1^k)^T \mathbf{W} \mathbf{h}_2^j, \qquad (2)$$

where  $\mathbf{W}$  is a learnable matrix. The loss we optimize is the multi-class cross entropy:

$$\mathcal{L} = -\sum_{k=1}^{K} \log \frac{\exp(\operatorname{sim}(\mathbf{h}_{1}^{k}, \mathbf{h}_{2}^{k}))}{\sum_{j=1}^{K} \exp(\operatorname{sim}(\mathbf{h}_{1}^{k}, \mathbf{h}_{2}^{j}))} \,.$$
(3)

We depict the training procedure of COCOLA in Figure 2 for the single stem case.

In the COLA training procedure, the positive pairs are (fully mixed) windows belonging to the same track. In COCOLA, they are sub-mixes belonging to the same window. As such, we allow for negative pairs belonging to the same track but in different windows. The r ratio has to be chosen well to

<sup>&</sup>lt;sup>2</sup>In our notation, we incorporate into  $f_{\theta}$  any domain transform preceding or following the convolutional network operations, like the (pre) mel-filterbank map and the (post) projection head g in COLA.

TABLE ICLASSIFICATION ACCURACY TESTS (%) WITH COCOLA MODELS USINGK = 2 SUB-MIXTURE TEST PAIRS (HIGHER IS BETTER). MUSDB18-HQIS USED AS A HOLD-OUT TEST DATASET.

|                   | Test Dataset |          |           |              |  |  |
|-------------------|--------------|----------|-----------|--------------|--|--|
| Model             | MUSDB18-HQ   | MoisesDB | Slakh2100 | CocoChorales |  |  |
| w\o HPS           |              |          |           |              |  |  |
| MoisesDB [35]     | 52.56        | 53.01    | 51.22     | 60.32        |  |  |
| Slakh2100 [36]    | 53.06        | 53.58    | 53.78     | 59.35        |  |  |
| CocoChorales [37] | 70.10        | 61.48    | 67.50     | 99.78        |  |  |
| All               | 90.43        | 93.06    | 90.06     | 99.89        |  |  |
| w\ HPS            |              |          |           |              |  |  |
| AlÌ               | 93.87        | 93.67    | 94.27     | 99.68        |  |  |

TABLE II CLASSIFICATION ACCURACY TESTS (%) WITH COCOLA HPS ALL VARYING THE VALUES OF K.

| Test Dataset |            |          |           |              |  |  |  |  |  |
|--------------|------------|----------|-----------|--------------|--|--|--|--|--|
| K            | MUSDB18-HQ | MoisesDB | Slakh2100 | CocoChorales |  |  |  |  |  |
| 8            | 78.02      | 73.68    | 79.72     | 98.27        |  |  |  |  |  |
| 16           | 70.32      | 62.17    | 72.62     | 96.67        |  |  |  |  |  |
| 64           | 54.33      | 34.04    | 59.35     | 90.67        |  |  |  |  |  |

avoid strong overlaps between windows in the same track. In that case, we could potentially consider (nearly) coherent submixes as negative pairs.

In addition to the standard mel-filterbank representation of the input (as defined in COLA), we propose a variant where the COCOLA encoder operates on a pair of mel spectrogram features obtained via harmonic-percussive separation (HPS) [38]. As shown in Section V, this factorized input not only improves performance but also lets us better interpret which factor (harmony or rhythm) is more coherent.

# B. COCOLA Score

Equipped with the encoder  $f_{\theta}$ , we can quantify the coherence of the accompaniments generated by a generative model  $p_{\phi}(\mathbf{x} \mid \mathbf{y})$ , where  $\mathbf{y}$  is the conditioning variable (the input) and  $\mathbf{x}$  is the modeled variable (the output). The model's variables can be either a set of stems or sub-mixes. Given the input  $\mathbf{y}$ , the model  $p_{\phi}$  generates an output  $\tilde{\mathbf{x}} \sim p_{\phi}(\mathbf{x} \mid \mathbf{y})$ . We can compute the coherence between  $\mathbf{y}$  and  $\tilde{\mathbf{x}}$  by first embedding the two vectors  $\mathbf{h}_{\mathbf{y}} = f_{\theta}(\mathbf{y})$  and  $\mathbf{h}_{\tilde{\mathbf{x}}} = f_{\theta}(\tilde{\mathbf{x}})$  (summing the stems beforehand if considering a set of stems). We define the *COCOLA Score* between  $\mathbf{x}$  and  $\tilde{\mathbf{y}}$  as  $sim(\mathbf{h}_{\mathbf{y}}, \mathbf{h}_{\tilde{\mathbf{x}}})$ , the similarity (Eq. (2)) between their embeddings. The described procedure is depicted in Figure 1.

#### IV. EXPERIMENTAL SETUP

# A. Datasets

In our experiments, we use four different stem-separated public datasets for training COCOLA. The datasets are MUSDB18-HQ [39], MoisesDB [35], Slakh2100 [36] and CocoChorales [37]. For MoisesDB, not having pre-determined splits, we set custom 0.8 (train) / 0.1 (validation) / 0.1 (test) splits. For CocoChorales, we use the tiny version, comprising a subset of 4000 tracks.



Fig. 3. Correlation plot between subjective scores (MOS) (x-axis) and COCOLA Scores (y-axis).

## B. Model Implementation

To implement the COCOLA encoder  $f_{\theta}$ , we follow the COLA framework [26] and employ the EfficientNet-B0 [40] (using two input channels for HPS) convolutional architecture followed by a linear projection layer. The embedding dimension is 512. Differently from the original baseline, we add a 0.1 dropout on the EfficientNet layers.

## C. Training Details

All COCOLA models are trained on an NVIDIA RTX 4070 Super with 12GB of VRAM. Each training batch contains 32 audio chunks of 5s (16kHz). We set the maximum window overlap ratio r = 50% and train with the Adam optimizer with a  $10^{-3}$  learning rate. As a data augmentation method, we add Gaussian noise to positive samples, with  $\sigma = 10^{-3}$ .

During the training with HPS, masking is randomly applied to either one of the two channels or none. This approach allows the model to learn representations from either component independently.

### V. EXPERIMENTS

In our experiments, we trained four COCOLA encoder models without HPS: "COCOLA MoisesDB", "COCOLA Slakh2100", "COCOLA CocoChorales" and "COCOLA All". The first three are trained on the homonym datasets, while the last one is trained on all three combined. For the "COCOLA CocoChorales" we use all ensembles, while on "COCOLA All" we use only the Random ensemble for a more balanced partitioning with respect to the other datasets. Additionally, we train a "COCOLA HPS All" model employing HPS with the same data as "COCOLA ALL". MUSDB18-HQ, being the smallest dataset, is used as a held-out test dataset for studying generalization.

#### A. Coherent Sub-Mix Classification

We cross-test the performance of COCOLA models trained without HPS by classifying coherent pairs on the test splits of our datasets. More specifically, given an encoder  $f_{\theta}$ , we iterate a test set, collecting at each step a batch of K windows

 TABLE III

 COMPARISON BETWEEN MUSIC ACCOMPANIMENT GENERATION MODELS.

| Method                  | FAD ↓<br>CLAP | FAD ↓<br>EnCodec | FAD ↓<br>VGGish | COCOLA Score↑<br>Percussive + Harmonic | COCOLA Score ↑<br>Percussive | COCOLA Score ↑<br>Harmonic |
|-------------------------|---------------|------------------|-----------------|----------------------------------------|------------------------------|----------------------------|
| MoisesDB Test           |               |                  |                 |                                        |                              |                            |
| Random                  | 0.072         | 19.37            | 0.38            | 50.53                                  | 52.34                        | 53.86                      |
| GMSDI [32]              | 0.37          | - 193.54         | 7.73            | - 45.29                                | - 46.67                      | 47.50                      |
| SA ControlNet [4], [42] | 0.15          | 170.21           | 2.59            | 55.11                                  | 55.89                        | 57.34                      |
| Diff-A-Riff [28]        | 0.14          | 12.16            | 0.90            | 57.34                                  | 58.00                        | 60.00                      |
| Ground Truth            |               |                  |                 | 57.70                                  | 58.66                        | 60.75                      |
| MUSDB18-HQ Test         |               |                  |                 |                                        |                              |                            |
| Random                  | 0.087         | 6.04             | 0.49            | 49.49                                  | 51.27                        | 51.32                      |
| GMSDI [9]               | 0.44          | 23.06            | 4.99            | 53.51                                  | 53.90                        | 54.51                      |
| SA ControlNet [4], [42] | 0.12          | 12.14            | 0.66            | 56.41                                  | 57.48                        | 58.82                      |
| Diff-A-Riff [28]        | 0.20          | 119.41           | 1.68            | 53.79                                  | 54.75                        | 56.08                      |
| Ground Truth            |               |                  |                 | 56.47                                  | 57.55                        | 58.94                      |

 $\mathbf{x}^1, \ldots, \mathbf{x}^K$ . Following the steps in Section III-A we compute all similarities  $sim(\mathbf{h}_1^k, \mathbf{h}_2^j)$  for  $k, j \in [K]$ . We define the accuracy over a batch as:

$$\frac{1}{K}\sum_{k=1}^{K}\mathbb{1}\left(k = \operatorname*{arg\,max}_{j \in [K]} \operatorname{sim}(\mathbf{h}_{1}^{k}, \mathbf{h}_{2}^{j})\right),\tag{4}$$

where 1 is the indicator function. We compute the final accuracy by averaging across all batches. Using K = 2, Table I shows results for various model and test dataset combinations. While "COCOLA MoisesDB" and "COCOLA Slakh2100" perform slightly better than random, "COCOLA Coco-Chorales" shows improved performance. Combining all three datasets achieves over 90% accuracy.

Adding HPS to "COCOLA All", all metrics improve except on CocoChorales (which is already high), reaching 93.87% on the held-out MUSDB18-HQ and showcasing the usefulness of the factorized representation. We also investigate the performance of "COCOLA HPS All" increasing K in Table II.

## **B.** Accompaniment Generation Evaluation

For the music accompaniment generation evaluation, we compare GMSDI [32], Diff-A-Riff [28], and Stable Audio ControlNet (SA ControlNet). The latter is an implementation of a DiT-based [41] ControlNet [42] for Stable Audio Open [4], which we release<sup>3</sup>, given the lack of state-of-the-art open-source models for music accompaniment generation (only MSDM [9] is available, but it is trained on Slakh2100 [36] not being applicable in realistic settings).

GMSDI is trained on MTG-Jamendo [43], Diff-A-Riff on a proprietary dataset and we finetune SA ControlNet on MoisesDB. We also consider a Random baseline, where, for a given input, we output a random stem from a different test chunk. We evaluate the models both on the MoisesDB and MUSDB18-HQ test splits.

We sample 168 chunks ( $\sim$ 47.55s) from the MoisesDB test split and 236 chunks of the same length from the MUSDB18-HQ test split, using random stem subsets as input and querying complementary stems, excluding vocals from the output and

<sup>3</sup>https://github.com/EmilianPostolache/stable-audio-controlnet

the "Other" class in MUSDB18-HQ. SA ControlNet processes the full chunk, while GMSDI and Diff-A-Riff use shorter initial sub-chunks ( $\sim$ 23.78s and  $\sim$ 9.58s, respectively) due to reduced context windows. Outputs are cut to the initial  $\sim$ 9.58s.

We compare the COCOLA Score (based on "COCOLA HPS All") with the FAD [14], [44] metric (interpreted as a sub-FAD [9], [13]), computed using CLAP [7], EnCodec [45], and VGGish. Results in Table III show that FAD tends to favor the Random baseline, as it evaluates perceptual quality but not track coherence, which is better captured by COCOLA. On Ground Truth, we compute COCOLA upper bounds with real positive pairs. Diff-A-Riff performs best on MoisesDB, and SA ControlNet on MUSDB18-HQ.

## C. MOS vs COCOLA Score

To evaluate COCOLA's effectiveness, we conducted a subjective test with 41 participants who rated (0-4) the coherence of (pitch) Shifted and (time) Stretched chunks. We also used Random, Ground Truth, Diff-A-Riff and SA ControlNet tracks from the previous experiment. We average the ratings (MOS) for each chunk. Figure 3 shows the correlation plot between MOS and COCOLA Score (using "COCOLA HPS All"). The Pearson correlation coefficient is r = 0.54 (p < 0.01) indicating a good correlation with high statistical significance.

## VI. CONCLUSION

In this paper, we proposed COCOLA, a contrastive encoder for recognizing the coherence between musical stems. Both classification experiments and human scores demonstrate the efficacy of the method. We used COCOLA for benchmarking music accompaniment models, proposing a new evaluation metric for the task. We plan to improve the quality of CO-COLA by training on additional stem-level datasets [46] or on pre-separated [13] large scale datasets [43].

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