Embedding Alignment in Code Generation for Audio

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ABSTRACT

LLM-powered code generation has the potential to revolutionize creative coding endeavors, such as live-coding, by enabling users to focus on structural motifs over syntactic details. In such domains, when prompting an LLM, users may benefit from considering multiple varied code candidates to better realize their musical intentions. Code generation models, however, struggle to present unique and diverse code candidates, with no direct insight into the code's audio output. To better establish a relationship between code candidates and produced audio, we investigate the topology of the mapping between code and audio embedding spaces. We find that code and audio embeddings do not exhibit a simple linear relationship, but supplement this with a constructed predictive model that shows an embedding alignment map could be learned. Supplementing the aim for musically diverse output, we present a model that given code predicts output audio embedding, constructing a code-audio embedding alignment map.

Keywords: Code Generation, Computer Music, Embedding Alignment

INTRODUCTION

Creative coding endeavours such as *live-coding* are emerging as a vibrant space at the intersection of art and computation, where multimedia-generating code is used as a medium for live artistic expression. Live coding as a medium emphasizes not only the final output but the creation process, inviting audiences to witness the artwork's construction as it unfolds; this is highlighted in the TOPLAP live coding manifesto [1]. Live coding environments are often tailored to be expressive and succinct, enabling performers to translate musical ideas into code with minimal friction. There exist many modern music programming languages, like Sonic Pi [2], SuperCollider [3] and Tidal Cycles [4], each taking the form of a specific Domain Specific Language (DSL). Our project considers Sonic Pi, a live coding DSL developed on Ruby, that is widely used for educational and artistic purposes.

LLM-powered code generation presents an exciting opportunity for such creative domains, where the emphasis is on expressive, real-time audiovisual performance. LLMs can help reduce the syntactic burden on performers, allowing them to focus on structural and creative motifs rather than low-level implementation details. However, current code generation systems often struggle to provide functionally unique and diverse code candidates, especially in multi-modal scenarios where the output of code is not text, but sound or video. Indeed, models showcase difficulty with comprehending musical notions [5]. This limitation is particularly significant in live coding, where output must align with the coder's intention.

A core challenge in applying LLMs to live coding is the model's lack of direct access to or sensory understanding of the output it produces. Code generation models typically evaluate or rank their output using text-based similarity metrics, which do not capture perceptual differences in audio. As a result, multiple candidate code snippets may be semantically diverse in structure but aurally redundant or indistinct. This disconnect between code and output similarity hinders the effectiveness of LLM support in multi-modal creative applications. Recent advances in embedding models offer a potential path forward. Embedding spaces for both code (CodeSearchNet [6]) and audio (wav2vec [7]) attempt to represent meaningful relationships by mapping entities to high-dimensional vectors where "similar" items are located close to each other. If we were to build an alignment map between code and audio, we would have a mechanism of reasoning about musical similarity only with produced code.

To explore this relationship, we propose a neural network model that predicts the distance between two audio embeddings based solely on the embeddings of their respective code. The goal is not to synthesize audio directly, but to model how changes in code embeddings affect the perceptual distance in their resulting audio outputs. Such a model can provide insights into the topology of the code-audio relationship and help bridge what a model "writes" and what a user "hears."

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RELATED WORK

Code Generation Models

With the rise of large language models (LLMs), models such as Github's CoPilot [8] and OpenAI's Codex [9] have shown significant code generation capabilities for complex programming tasks. Tailored for code generation tasks, these models have been trained on large code repositories and fine-tuned to mimic code semantic structures. Code generation models have generally been trained for competitive programming tasks, with the OpenAI dataset HumanEval one of the predominant evaluation benchmark [9]. Recent works have explored code generation for music computing and impacts towards coding sentiments [10]. Due to the face that LLMs are non-deterministic, code correctness and consistency remains a challenging problem [11]. These problems are exasperated in creative coding frameworks, with less data to train for certain Domain Specific Languages (DSLs). LLMs have shown to struggle with music comprehension [12], suggesting they may struggle to evaluate the generated computer music code.

Music Programming Languages

Many modern music programming languages take the form of DSLs (domain specific languages) - languages that are designed for a specific application domain. One such example is SuperCollider, an audio programming language and environment for real-time audio synthesis and algorithmic composition [13]. Conversely, FAUST (Functional AUdio STream) is a purely functional programming language for real-time signal processing [14].

Live coding languages are a subset of music programming languages tailored for live music performance. One example is Sonic Pi, a live coding language built on Ruby that has been prominently adopted by the community. Sonic Pi has shown promise in educational settings, introducing students to computer science concepts through real-time music coding [15]. Tidal Cycles is another functional alternative built on the Haskell functional programming language; it offers programmers a declarative approach to live coding [16]. As is the case with general purpose music programming languages, live coding languages make design decisions with the aim of providing a better interface to users to express their intention. Our work is similar to language design in that we explore the potential of LLMs to make live coding less syntactically burdened.

Embedding Space Alignment

Embedding models have garnered significant attention from the Natural Language Processing (NLP) space, with important applications to LLMs and other deep learning techniques. Succinctly, embedding models attempt to produce learned dimensional representations of data in some hyperplane. Pre-trained embedding models have been employed to map data - words, images, audio files, programs - into vector spaces that encode relational semantics. Program embedding models have been applied to augment code-classification and auto-completion [17]. Similarly, audio embedding models have been considered for speech recognition, music generation, and audio classification [18]. Audio embedding models capture acoustic features and temporal dependencies, with different models highlighting different auditory features [19, 20]. The nature of embeddings makes it so that encoded variations may not reflect perceptible differences - certain works have investigated this fact in both audio and program domains [21].

Given two embeddings in different vector hyperplanes, one then may inquire about their relationship - this is the aim of embedding space alignment. Early alignment methods applied to language and knowledge graphs sought to formally establish linear relationships between these spaces; however, recent efforts on more complex maps have employed unsupervised methods [22]. With the rise of multi-modal LLMs, cross-modal alignment has begun to appear in audio visual domains [21]. Novel works have explored ways of encoding linguistic semantics in audio embeddings, and have even presented joint embedding spaces between the two fields [23, 24].

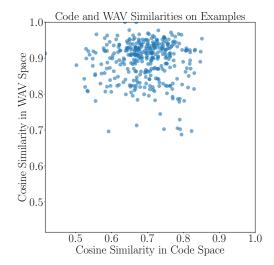
PRELIMINARY INVESTIGATION

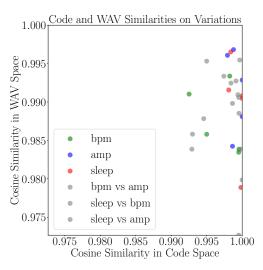
In our pursuit of an embedding alignment map, we first investigate the topological relationship between code and audio embeddings. In doing so, we garner a sense of our latent space and are better equipped to determine a suitable model for this embedding alignment map.

As an initial study, we construct a dataset of code-audio pairs, from which we extract respective embedding values. We collate this data, visualizing the results and extracting correlative statistics. We

select benchmarks from the Sonic Pi tutorials and record the corresponding audio outputs. We chose Sonic Pi due to its prominence, terseness, and strong documentation, with a preliminary investigation finding that code-generation models seem to perform better with it than other computer-music DSLs. The dataset we consider consists of 28 distinct programs from the Sonic Pi environment and a corresponding set of 28 audio files. For each audio clip, we extract the first nine measures at a fixed tempo of 120 BPM, ensuring that audio content is captured in a standardized manner. Using an automated script, we simultaneously load both the audio clips and their associated program code, computing embeddings for each entry.

We extract code and audio embeddings using distilroberta-base [25] and Meta's wav2vec2 model [7]. Retrieving the code-audio embeddings, we assess the degree of similarity between pair embedding values by considering embedding cosine similarity. We compute Pearson and Spearman correlation coefficients based on the similarity scores of the samples.





- **(a)** Embedding distances between all pairs of SonicPi Examples.
- **(b)** Embedding distances between all pairs of small code variations.

Figure 1. Plotting distances between samples in both embedding spaces shows that mapping between spaces is nontrivial.

Figure 1a presents the results of our investigation, plotting the cosine similarity scores of all code pair embeddings and their respective audio embeddings for a total of 378 entries. Looking at the results, we establish that no evident relationship is emergent. Computation of the Pearson correlation (0.0159, p=0.7670) and the Spearman correlation (0.0409, p=0.4450) confirm the lack of any linear or rank order relationship. These results suggest that there is no simple embedding alignment map between code and audio domains. This matches our conceptual intuition of embedding alignment - a perfect alignment would fully encode the Sonic Pi compiler and audio engine.

Having conducted a coarse-grained study, we find no simple relationship between code and audio embeddings exists. We proceed to conduct a more fine-grained analysis investigating the sensitivity of code and audio embeddings to small modifications in the program code. In doing so, we garner a more acute understanding of how differences in code affect the resultant audio embeddings.

For this investigation, we analyze the six longest programs from the dataset. We modify these artifacts by varying the values of three parameters: sleep time, amplitude (amp), and beats per minute (bpm). These parameters were present across all artifacts, ensuring consistent evaluation. We posit that minor code modifications should yield similar code embedding, but may present varying degrees of changes to the audio embeddings, depending on the altered variable. Changing amplitude, for instance, should affect produced audio less than changes in sleep, which may change syncopation entirely.

Figure 1b displays the cosine similarities of code variations in the code and audio embedding space. In line with our hypothesis, variant code artifacts maintain a high similarity, with code similarity scores remaining above 0.990. While cosine similarity also remains relatively high in the audio embedding space, the exhibited range is larger, with similarity scores below 0.975. Interestingly, there is no perceptible trend between variable changes and resultant audio embedding. Sleep, bpm, and amp variations all exhibit

fluctuating changes in the audio embedding space. As was the case with the previous study, our data yields exceedingly low Pearson and Spearman correlations. The associative, albeit not equivalent, range compression of both code and wav embedding distances suggests some coarse association between the domains, however, such an association is evidently neither linear nor monotonic.

DATA AUGMENTATION

Investigating the complex code-audio embedding relationship, we ascertain that a black-box model solution would best suit the construction of an embedding alignment map. In order to train such a Multi-Layer Perceptron (MLP) model, we require a large amount of Sonic Pi code and respective audio samples. Manually constructing these artifacts is intractable, and there is little in the way of a clean, extensive Sonic Pi dataset. The best candidate for such a dataset comes from the 28 Sonic Pi tutorial entries. Most of these are examples written by Sam Aaron, the creator of Sonic Pi, to showcase the framework's capabilities, while the rest are examples added by the community. While the dataset entries are clean and diverse, we do not have nearly enough to train a model. As a result, we explore augmenting our dataset employing templates.

Templates

Using the Jinja engine [26], we transformed each of the 28 examples into a template by randomizing various parameters like sample type, synthesizer used, scale character, effects used, notes, and timers. A template example can be seen in Listing 1, where we used *compus beats* coded by Sam Aaron and changed several values with templated parameters. In Table 1, we list a few of the parameters used as templates, with some example values. Our dataset generation code includes additional templates for various float values, like sleep durations, amplification values, and range number values.

Listing 1. Jinja Template used for the Compus Beats example

```
# Compus Beats
# Coded by Sam Aaron
use_sample_bpm :{{samples_bpm[0]}}, num_beats: {{repeat_small_ints[0]}}
live_loop :loopr do
 sample :{{samples_bpm[0]}}, rate: [0.5, 1, 1, 1, 1, 2].choose unless
     one in(10)
 sleep {{sleep_values[0]}}
end
live_loop :bass do
 sample :{{sample_values[0]}}, amp: rrand(0.1, 0.2), rate: [0.5, 0.5, 1,
     1,2,4].choose if one_in(4)
 use_synth :{{synth_values[0]}}
 use_synth_defaults mod_invert_wave: 1
 play :{{note_values[0]}}, mod_range: 12, amp: rrand(0.5, 1), mod_phase:
     [0.25, 0.5, 1].choose, release: {{release_values[(1)% release_values|
     length]}}, cutoff: rrand(50, 90)
 play :{{note_values[(1) % note_values|length]}}, mod_range: [24, 36, 34].
     choose, amp: {{amp_values[0]}}, mod_phase: 0.25, release: {{
     release_values[0]}}, cutoff: {{repeat_large_ints[0]}}, pulse_width:
     rand
 sleep {{sleep_values[(1)% sleep_values|length]}}
end
```

Code Generation

Using the values described above and a simple Python script utilizing Jinja, we rendered **200** different code files (.pi extension) for each one of the 28 examples. For each .pi file, the values are regenerated

Parameters	Example Values		
samples	ambi_choir, bass_voxy_c		
synths	beep, rodeo		
character	major, minor		
attack_range	0 - 10		
effects	echo, compressor		
notes	C2, Db2,, C6		

Table 1. Parameters used for templating

randomly, so we obtain a set of different code files for each created template. Therefore, since we used 28 templates and generated 200 code files for each, we initially gathered 5600 .pi files.

Audio Generation

To generate audio for each one of the 5600 code files, we had to avoid using the Sonic Pi program directly, as it would require too much manual effort and time. Automating the audio generation process through the Python programming language required us to utilize the Python-Sonic interface [27], which connects to a running Sonic Pi instance and lets us run and record .pi code via a Python API. Thus, using this API, we aimed to generate a 10-second recording for each of the 5600 code files. A limitation of Python-Sonic is that the interpreter does not issue an exception if we provide Sonic Pi with a code file that cannot be played (e.g. due to invalid value configurations). This is attributed to Sonic Pi's design, which uses the Open Sound Control (OSC) protocol to send the .pi file to a Ruby-based server and then to SuperCollider's scsynth engine for playback. Since we generate many different parameters randomly, we may create configurations that cause SuperCollider errors, for which Sonic Pi does not produce any audio. Thus, from the 5600 initial code files, we generated 5400 valid recordings.

Embedding Generation

The final step required generating the embeddings for both code and audio files. We used the code search model distilroberta-base [25] to generate the code embeddings for each .pi file and Meta's wav2vec2 [7] to extract the audio embeddings from the respective recordings. Audio embeddings were sampled at a 16 kHz rate for homogeneity. Following this process, we created an arrow dataset which contains the code .pi description, the code embedding and audio embedding of 5400 samples.

MODEL IMPLEMENTATION

To align code and audio embeddings into a shared latent space, we adopt a symmetric architecture consisting of two independent Multi-Layer Perceptrons (MLPs): one for code embeddings \mathtt{MLP}_c and one for audio embeddings \mathtt{MLP}_a . Both networks take as input the respective modality's pretrained embeddings and project them into a common embedding space of dimension d_{out} .

Each MLP consists of L linear layers, with intermediate hidden layers of dimension d_{hidden} , each followed by BatchNorm and GELU activations. We use BatchNorm to stabilize training by normalizing activations across the batch, and GELU as the activation function due to its smooth, non-linear behavior that improves gradient flow and empirical performance over ReLU in deep networks. We project the pre-trained code and audio embeddings as

$$c_i = \text{MLP}_c(c_i^0)$$
 $a_i = \text{MLP}_a(a_i^0)$

where, c_i^0 and a_i^0 are the embeddings extracted from the pretrained model, and c_i and a_i are the aligned embeddings. This simple formulation was selected for its ability to capture nonlinear transformations without introducing architectural biases toward either modality. Unlike attention-based architectures, MLPs offer an efficient way to map pretrained embeddings into an aligned representation space.

To train the models, we employ the **InfoNCE loss**, a contrastive learning objective that brings semantically aligned code-audio pairs closer while pushing apart mismatched pairs in the same batch. This choice is motivated by the need for self-supervised alignment, where explicit labels are not available, but semantic consistency can be inferred from pairing.

Given a batch of N aligned code-audio embeddings $\{(c_i, a_i)\}_{i=1}^N$, we define cosine similarity as:

$$\operatorname{sim}(c_i, a_j) = \frac{c_i^{\top} a_j}{\|c_i\| \cdot \|a_j\|}.$$
 (1)

The InfoNCE loss for a single positive pair (c_i, a_i) is:

$$\mathcal{L}_i = -\log \frac{\exp(\sin(c_i, a_i)/\tau)}{\sum_{j=1}^N \exp(\sin(c_i, a_j)/\tau)},\tag{2}$$

where τ is a temperature hyperparameter that controls the sharpness of the similarity distribution. The overall loss is computed as:

$$\mathcal{L} = \frac{1}{N} \sum_{i=1}^{N} \mathcal{L}_i. \tag{3}$$

This contrastive formulation is particularly effective in our setting, where each code-audio pair is semantically meaningful, but hard supervision is unavailable. InfoNCE encourages the model to preserve these pairwise relationships and learn embeddings that are useful for downstream retrieval and matching tasks.

EVALUATION

To quantify the alignment between learned representations, we utilize two additional similarity metrics: Canonical Correlation Analysis (CCA) and Centered Kernel Alignment (CKA).

CCA measures the maximum linear correlation between two multivariate random variables after projecting them onto a shared subspace. In our context, given code and audio embeddings C and A, CCA finds linear projections such that the correlation between Cw_c and Aw_a is maximized. The resulting correlation scores reflect the extent to which a linear transformation can align the two modalities. To ensure comparability across configurations, we normalize CCA scores by the embedding dimensionality.

CKA, on the other hand, captures similarities between representations in a way that is invariant to orthogonal transformations and isotropic scaling. Unlike CCA, which measures linear alignment, CKA is sensitive to more general (nonlinear) structural similarities. It operates on kernel matrices K and L derived from embeddings and computes:

$$CKA(K,L) = \frac{\langle K_c, L_c \rangle_F}{\|K_c\|_F \cdot \|L_c\|_F},\tag{4}$$

where K_c and L_c are centered versions of the kernel matrices, and $\langle \cdot, \cdot \rangle_F$ denotes the Frobenius inner product. A CKA score close to 1 indicates high structural similarity between representations.

By combining InfoNCE-based contrastive training with post-hoc evaluation using CKA and normalized CCA, we comprehensively assess the degree to which learned embeddings from the code and audio modalities are aligned at both linear and structural levels.

Table 2 presents the results of hyperparameter tuning for aligning code and waveform embeddings using a contrastive learning framework. The first row shows the pre-alignment metrics, where the average CKA and CCA are computed between raw, untrained embeddings. For the remaining rows, we report post-alignment CKA and CCA values across 24 hyperparameter configurations, each varying in hidden dimension, output dimension, number of layers, and learning rate. CCA values are normalized by the output dimension to ensure comparability across configurations. We report the mean and standard deviation over three independent runs. The best-performing configuration in terms of post-alignment CKA and CCA is highlighted in bold, while the second-best is underlined. Notably, configuration 21 achieved the highest CKA (0.590), indicating strong representational similarity post-alignment, and configuration 24 achieved the highest normalized CCA (0.902), reflecting excellent linear alignment between modalities.

The results in Table 2 indicate that our model successfully learns to align code and audio embeddings. Initially, the CKA between the two modalities was low (0.090), and the CCA score was only 0.140, suggesting minimal structural or linear correlation between the raw, untrained embeddings. After training with InfoNCE, the best configuration achieved a CKA of 0.590 and a normalized CCA of 0.902,

demonstrating a substantial increase in both representational and linear similarity. Compared to the initial embeddings, the final model achieves a six-fold improvement in CKA and a more than six-fold improvement in CCA, highlighting the effectiveness of the learned alignment. These improvements imply that our model has learned a meaningful shared embedding space, where, given a code embedding, one can reliably approximate the corresponding audio embedding. Although this does not constitute a perfect prediction, it shows strong alignment, especially considering the lack of explicit supervision.

Table 2. CCA and CKA comparison across a set of hyperparameters. The first row shows pre-alignment metrics. Best post-alignment results are in **bold** (1st) and <u>underlined</u> (2nd).

Config	d_{hidden}	d_{out}	L	LR	CKA	CCA
_	_	_	_	Before training	0.090 ± 0.001	0.145 ± 0.003
1	256	128	5	1e-4	0.420 ± 0.019	0.523 ± 0.021
2	128	64	1	1e-3	0.455 ± 0.004	0.480 ± 0.004
3	128	64	1	1e-4	0.463 ± 0.011	0.378 ± 0.011
4	128	64	3	1e-3	0.424 ± 0.024	0.510 ± 0.019
5	128	64	3	1e-4	0.398 ± 0.021	0.372 ± 0.010
6	128	64	5	1e-3	0.422 ± 0.014	0.552 ± 0.009
7	128	64	5	1e-4	0.357 ± 0.040	0.396 ± 0.011
8	128	128	1	1e-3	0.472 ± 0.057	0.660 ± 0.021
9	128	128	1	1e-4	0.490 ± 0.033	0.522 ± 0.010
10	128	128	3	1e-3	0.494 ± 0.017	0.691 ± 0.010
11	128	128	3	1e-4	0.459 ± 0.031	0.547 ± 0.003
12	128	128	5	1e-3	0.410 ± 0.023	0.735 ± 0.013
13	128	128	5	1e-4	0.407 ± 0.055	0.571 ± 0.013
14	256	64	1	1e-3	0.468 ± 0.063	0.499 ± 0.011
15	256	64	1	1e-4	0.514 ± 0.014	0.357 ± 0.005
16	256	64	3	1e-3	0.461 ± 0.035	0.556 ± 0.007
17	256	64	3	1e-4	0.454 ± 0.027	0.366 ± 0.006
18	256	64	5	1e-3	0.432 ± 0.005	0.644 ± 0.013
19	256	64	5	1e-4	0.386 ± 0.014	0.372 ± 0.010
20	256	128	1	1e-3	0.444 ± 0.042	0.736 ± 0.034
21	256	128	1	1e-4	$\textbf{0.590} \pm \textbf{0.044}$	0.486 ± 0.007
22	256	128	3	1e-3	0.444 ± 0.021	0.743 ± 0.045
23	256	128	3	1e-4	0.548 ± 0.033	0.493 ± 0.005
24	256	128	5	1e-3	0.466 ± 0.007	$\textbf{0.902} \pm \textbf{0.007}$

CONCLUSION

In this work, we examine the ability of LLMs to assist users with live coding. We aimed to show whether a model can produce variable code suggestions based on code and audio embeddings. To investigate this hypothesis, we utilized the Sonic Pi live coding framework and created a curated dataset of code-audio embeddings, using templates. We used two independent Multi-Layer Perceptrons and quantified the evaluation results using the Canonical Correlation Analysis and Centered Kernel Alignment metrics. Our results showcase that our neural network model successfully learns to align code and audio embeddings and can reliably approximate the audio embedding given the corresponding code embedding.

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