Computational Copyright: Towards A Royalty Model for Music Generative AI

Abstract

The advancement of generative AI has given rise to pressing copyright challenges, especially within the music industry. This paper focuses on the economic aspects of these challenges, emphasizing that the economic impact constitutes a central issue in the copyright arena. Furthermore, the complexity of the black-box generative AI technologies not only suggests but necessitates algorithmic solutions. Yet, such solutions have been largely missing, exacerbating regulatory hurdles in this landscape. We seek to address this gap by proposing viable royalty models for revenue sharing on AI music generation platforms. We start by examining existing royalty models utilized by platforms like Spotify and YouTube, and then discuss how to adapt them to the unique context of AI-generated music. A significant challenge emerging from this adaptation is the attribution of AI-generated music to influential copyrighted content in the training data. To this end, we present algorithmic solutions employing data attribution techniques. We also conduct a range of experiments to verify the effectiveness of these solutions. This research is one of the early attempts to integrate technical advancements with economic and legal considerations in the field of music generative AI, offering a computational copyright solution for the challenges posed by the opaque nature of AI technologies.

1. Introduction

Recent advancements in generative AI have significantly impacted creative industries, leading to a surge in AI-generated content across art, music, literature, and software. This rapid evolution has raised complex legal challenges, especially concerning copyright issues (Henderson et al., 2023; Samuelson, 2023; Sag, 2023; Franceschelli & Musolesi, 2022). A notable instance of these challenges is the recent lawsuit filed by New York Times against Microsoft and OpenAI (NYT, 2023). Copyright laws cover a range of rights, including protection of original works, controlling their reproduction, and managing the distribution of profits from these works. The emergence of generative AI poses multifaceted challenges in this regard, as it blurs the lines of authorship and originality.

Arguably, central to these challenges is the economic impact. Taking the music industry as an example, a vast collection of music has been publicly available on platforms like Spotify and YouTube, where copyright owners are compensated through royalties. This practice not only suggests that economic incentives are a primary reason for making music publicly accessible, but also highlights the centrality of economic rights in copyright protections. This trend is reflective of a broader truth: economic considerations are at the heart of the U.S. copyright law, where a primary goal is to stimulate creativity by ensuring that creators are adequately compensated. There has also been ongoing debate about whether training generative AI with copyrighted content aligns with the *fair use* doctrine. [1] However, it is increasingly argued that fair use may not apply if the AI generated content competes with the original market for the data (Henderson et al., 2023). These issues underscore the economic impact as a crucial aspect of copyright challenges in generative AI.

This paper aims to bridge this crucial gap by proposing potential royalty models for revenue sharing from AI music generation platforms. Specifically, we design the royalty model by addressing the following key questions: 1) Who are the stakeholders? 2) What are the sources of revenue? 3) How to determine the royalty distribution for revenue sharing? To answer these questions, we start with case studies of Spotify and YouTube, which are the leading platforms in music streaming and video sharing respectively. We investigate their royalty models and examine feasibility of adapting these models to AI music generation platforms. A critical technical challenge for such adaptation we identify is the difficulty in attributing the AI generated music to the influential copyrighted content used in the model training data. In response, we develop algorithmic solutions using data attribution techniques to mitigate these challenges. Our experimental results demonstrate that the proposed solutions are reasonably effective.

[1] See Section 107 of the Copyright Act: `https://www.copyright.gov/title17/92chap1.html#107`.

2. Royalty Model

2.1. Case Study: Spotify

Spotify employs a centralized method for sharing its revenue with copyright owners, primarily via *streaming royalties*. The process involves determining Spotify's total revenue from various sources, e.g., subscribers and advertisers, and subsequently calculating the royalty distribution pro rata for copyright owners.

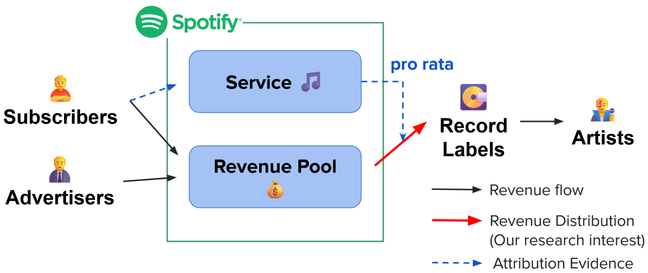

Figure 1. Spotify royalty model. The pro rata share of each copyrighted music can be calculated by the frequency of music play.

2.2. Case Study: YouTube

YouTube's model for compensating music copyright owners is multifaceted, here we focus on one of the most prominent one. The total revenue is first distributed to the videos, and then to the copyright owners whose music is used in the videos. This royalty mechanism relies on the *Content ID* system, which uses fingerprinting and machine learning to identify copyrighted content in uploaded videos and distribute revenue from these videos to the copyright owners.

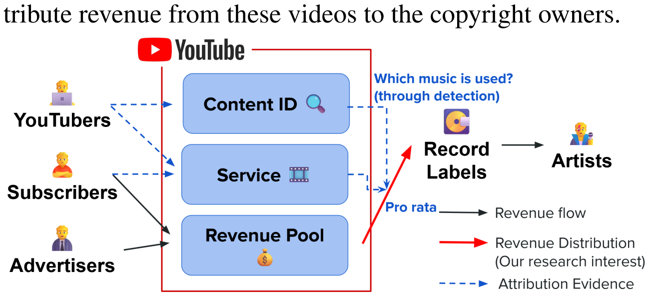

Figure 2. YouTube royalty model. The pro rata share of each copyrighted music relies on the Content ID system to attribute the videos back to the music included in the videos.

2.3. A Potential Royalty Model for AI Music Generation Platforms

In both case studies above, the platforms first gather a total revenue pool and then share the revenue with music copyright owners in proportion to the frequency that the music is accessed (either through direct playing or through videos). Having a similar royalty model for AI music generation platforms presents an open technical challenge: how to properly quantify the frequency of "access" for a piece of copyrighted music, which is used in the training corpus of the AI models, in the services. To address this challenge, we propose to use *data attribution* techniques, which measures the influence of individual training data points on each model generation, to attribute the frequency of access of generated music back to the copyrighted training pieces.

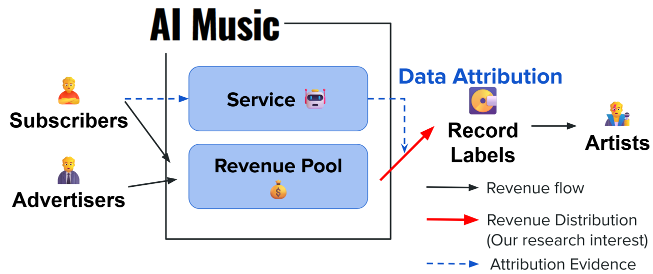

Figure 3. AI music platform royalty model. We propose to use data attribution to facilitate the calculation of the pro rata share.

3. Attributing AI-Generated Music to Copyrighted Training Content

We adapt two data attribution methods for classification models, TracIN (Pruthi et al., 2020) and TRAK (Park et al., 2023), to the Music Transformer model (Huang et al., 2018), and conduct experiments on the MAESTRO dataset (Hawthorne et al., 2019). Our results demonstrate that the proposed adaptations achieve decent attribution accuracy (Table 1) and the attribution results align well with some music-domain-specific heuristic metrics (Figure 4), hence showing the proposed method as a promising solution for mitigating the copyright issues of generative AI.

	Random	TracIN	TRAK
Segment-level	0.0091±0.007	-0.036± 0.031	**0.301±0.007**
Event-level	-0.0004±0.008	0.127±0.008	**0.359±0.010**

Table 1. The average retraining rank correlation (LDS (Park et al., 2023)) among 178 generated music for different data attribution methods. "Random" refers to a baseline that employs random attribution scores. "Segment-level" and "Event-level" refer to the granularity of attribution. The TRAK method achieves significantly good attribution performance for the music generation model.

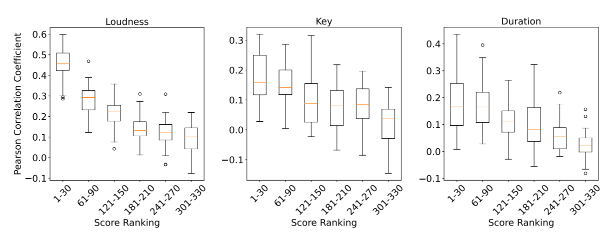

Figure 4. Musical similarity between the training music and the generated music in terms of loudness, key, and duration. The x-axis represents groups of training music pieces with decreasing attribution scores. The results indicate that the influential training music pieces identified by high data attribution scores are more similar with the generated music in terms of musical styles than the rest of the training corpus.

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