HarmonyCloak

Gaslighting Generative Audio Models

Silas Wang ; NYU GenAudio

Agenda

1. Issue(s) at Large
   a.) Automation
   b.) Privacy
   c.) The Arts
   d.) Threat Model
2. Preliminaries
   a.) Psychoacoustics
   b.) AI Overview
   c.) Adversarial Machine Learning
3. HarmonyCloak
   a.) Design
   b.) Harmony Cloak & MIDI/Audio
   c.) Optimization
   d.) Evaluation

Slides, Notes, References:

tinyurl.com/genaudio-harmonycloak

Issue(s) at Large

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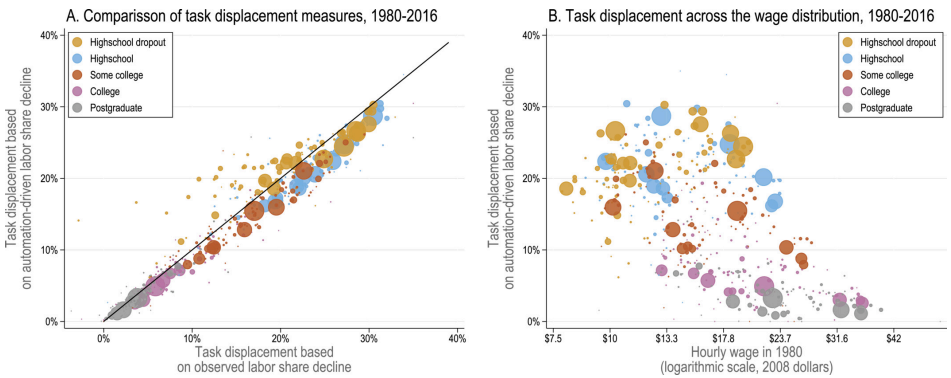
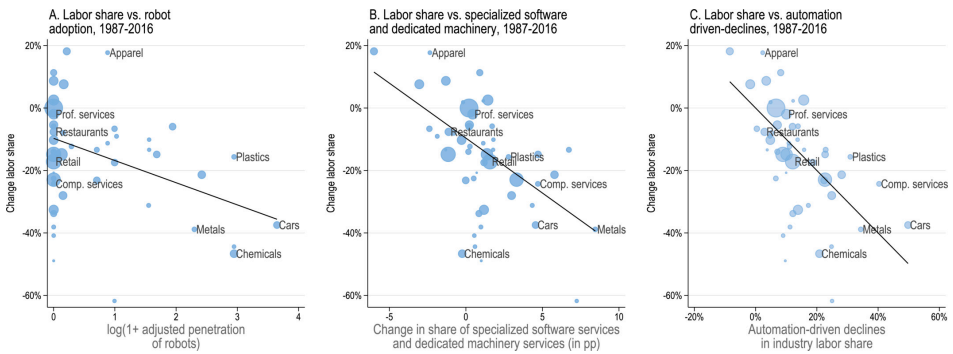
technology is advancing fast enough to outpace our measures for the displaced

Automation



Task Displacement by Education



Labor share & Automation

Self Driving Trucks

Millionaires' Row, Cleveland Ohio

Privacy

Government investment(s) in Surveillance

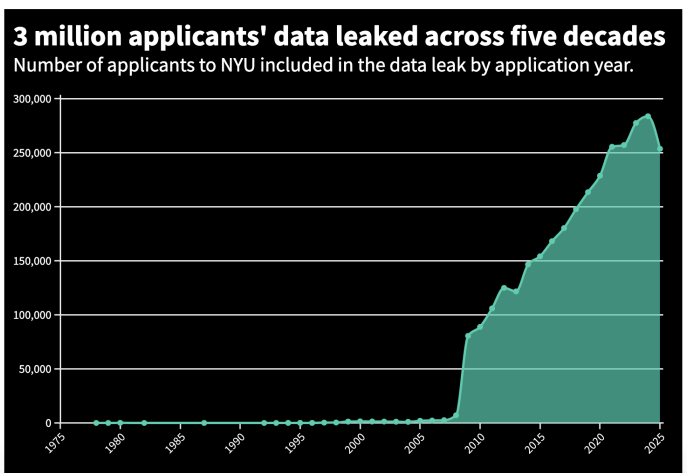
AI-driven Surveillance False Positives

NYU hit with 10 class action lawsuits following data breach

The plaintiffs are accusing the university of failing to protect personal information after a hacker leaked over 3 million applicants' data on NYU's homepage.

Dharma Niles and Krish Dev

April 1, 2025

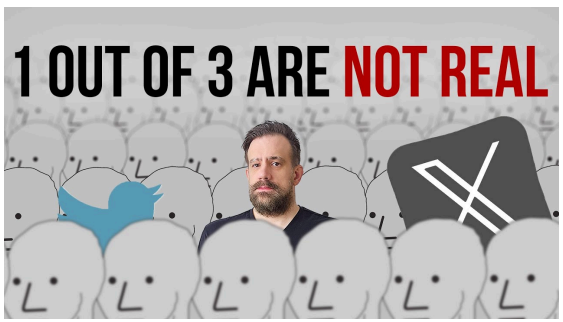


Poorly managing sensitive data

… and Misinformation

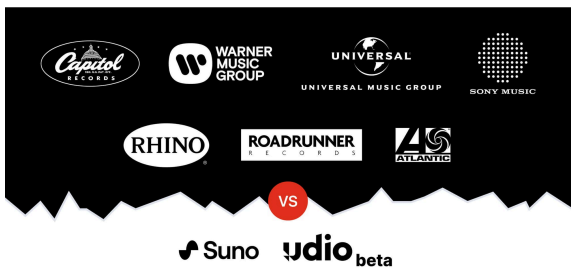
AI Voice Deepfake Scams

This Deepfake Scandal

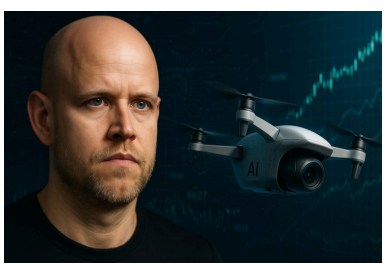


Dead Internet Theory

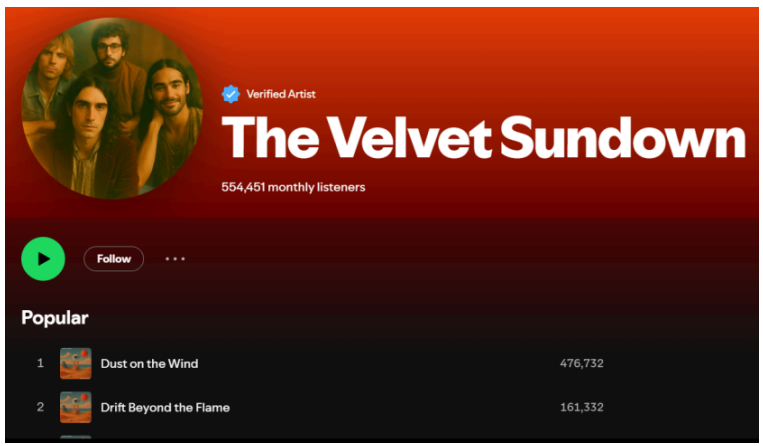
The Arts



Everybody's Favorite Music Lawsuit



Spotify Drone Investments



Everybody's Favorite Human Band

Threat Model

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Attacker's Capability:

- Scrape music from the internet to train Generative AI models
- Copyright infringement, musicians do not get paid

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Defender's Capabilities:

- Computer
- Can write and share songs
- Knowledge of the generative model[1]

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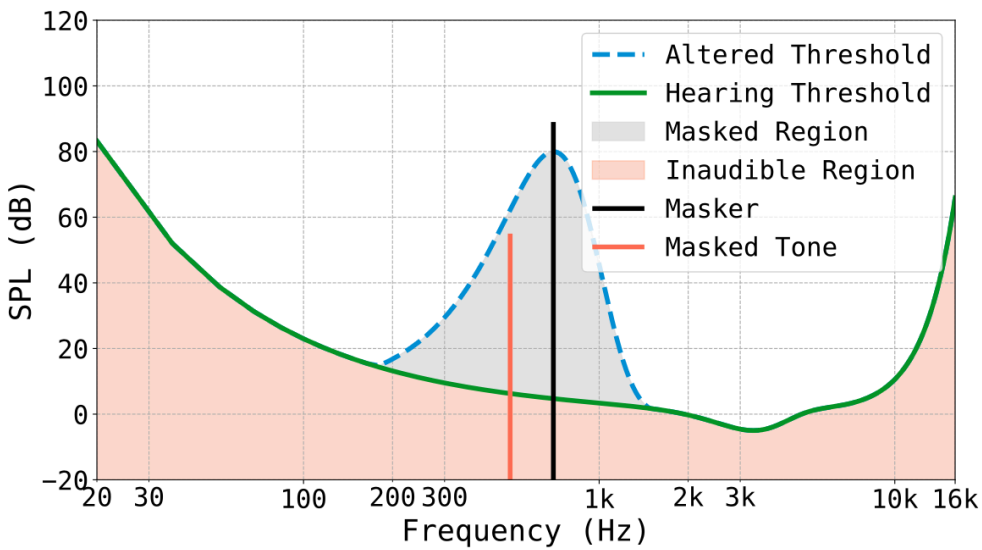
Preliminaries

Psychoacoustics

Psychoacoustics

Human hearing has a lower limit; a softest sound we can possibly hear. This **absolute hearing threshold** can be described mathematically for any frequency f:

$$T_H(f) = 3.64 \cdot \left(\frac{f}{1000}\right)^{-0.8} - 6.5 \cdot e^{-0.6\left(\frac{f}{1000}-3.3\right)^2}$$



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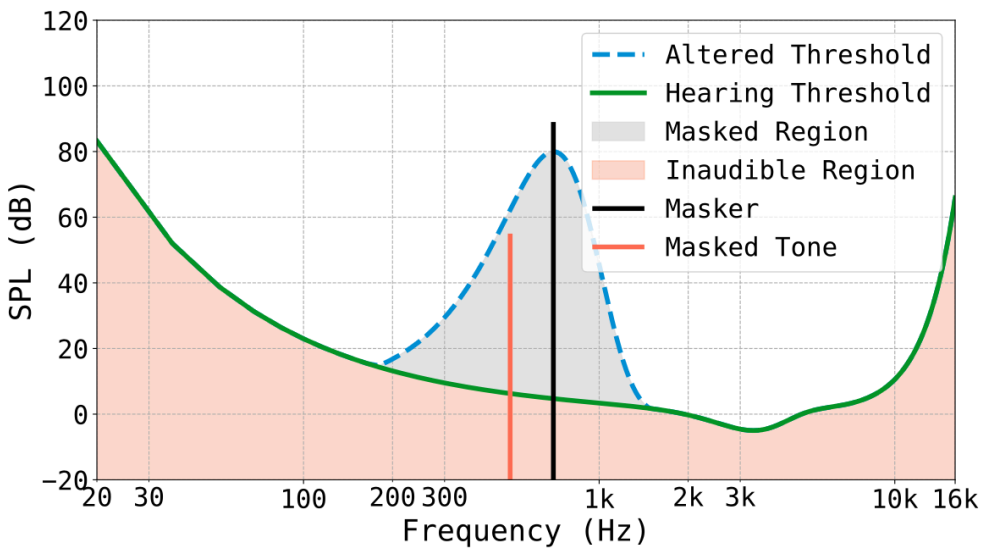
Additionally, given two sounds A and B with similar frequency ($f_A \approx f_B$), we say that A **masks** B if we can hear A but not B.

- **Temporal Masking** can also happen if A and B are not played at the same time.



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- MusicGen: Transformer-based model that generates audio from text (Flexible, Open Source, Meta)

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4. The noise must not degrade under compression algorithms

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HarmonyCloak with MIDI

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4. Enjoy a cup of hot chocolate and get a good night's rest.

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5. Enjoy a cup of hot chocolate and work on your GenAudio Projects

Loss Function and Optimizations

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$$\min_{\theta} \mathbb{E}\Big[\min_{\delta} \mathcal{L}_{gen}(f(x+\delta))\Big] + \alpha \sum_{m=1}^{M} w^m \parallel \delta^m \parallel_2 \text{ (generate the noise)}$$

such that

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where

$$\mathcal{H}\Big(T_{H(v)}\Big) = 127 \cdot 10^{\frac{1}{4}\log_{10}\left(T_{H(v)}\right) - L_U + 94} \text{ (constrain the magnitude, given note velocity fo for audior MIDI)}$$

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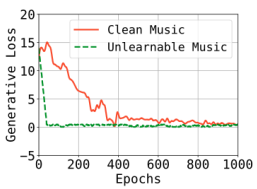
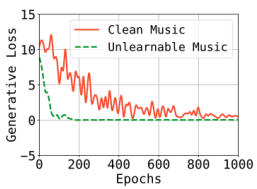
in other words, this is how we mathematically describe the high level stuff we have been building up to

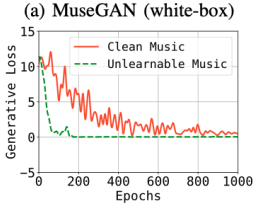
Evaluation



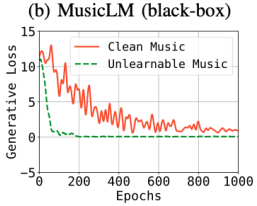
(a) MuseGAN (white-box)



(b) MusicLM (black-box)



(c) SymphonyNet (white-box)



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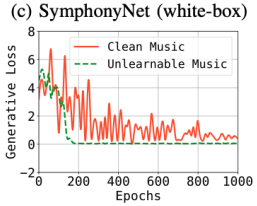
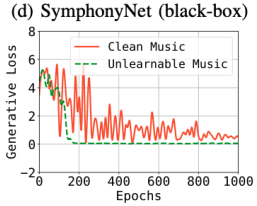


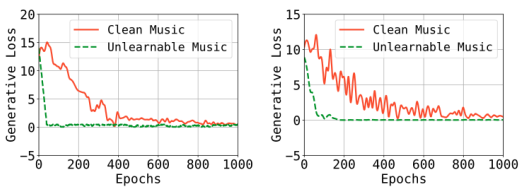
(e) MusicLM (white-box)



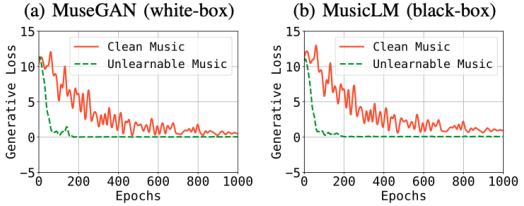
(f) MusicLM (black-box)

Settings	Music	Model	Avg. User Rating			
			H↑	P↑	N↑	OR↑
	Clean Training Music	-	4.17	4.81	4.19	4.45
	Generated Music (Trained on Clean Music)	MuseGAN	4.11	4.05	4.44	4.17
		SymphonyNet	4.44	4.53	4.20	4.11
		MusicLM	4.55	4.49	4.29	4.31
White-box	Unlearnable Training Music	-	4.11	4.72	4.01	4.32
	Generated Music (Trained on Unlearnable Music)	MuseGAN	2.34	3.10	1.20	2.40
		SymphonyNet	2.20	2.94	2.25	2.22
		MusicLM	3.22	3.10	2.29	2.31
Black-box	Unlearnable Training Music	-	4.03	4.45	3.98	4.12
	Generated Music (Trained on Unlearnable Music)	MuseGAN	2.44	3.78	1.94	2.88
		SymphonyNet	2.20	2.94	2.45	2.22
		MusicLM	3.41	3.04	2.78	2.34

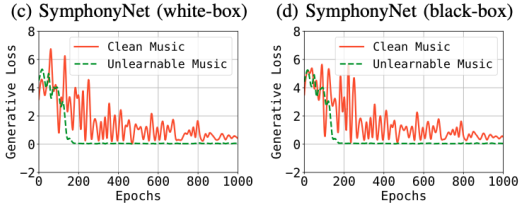
Evaluation



(a) MuseGAN (white-box) (b) MusicLM (black-box)



(c) SymphonyNet (white-box) (d) SymphonyNet (black-box)



(e) MusicLM (white-box) (f) MusicLM (black-box)

Settings	Music	Model	Avg. User Rating			
			H↑	P↑	N↑	OR↑
	Clean Training Music	-	4.17	4.81	4.19	4.45
	Generated Music (Trained on Clean Music)	MuseGAN	4.11	4.05	4.44	4.17
		SymphonyNet	4.44	4.53	4.20	4.11
		MusicLM	4.55	4.49	4.29	4.31
White-box	Unlearnable Training Music	-	4.11	4.72	4.01	4.32
	Generated Music (Trained on Unlearnable Music)	MuseGAN	2.34	3.10	1.20	2.40
		SymphonyNet	2.20	2.94	2.25	2.22
		MusicLM	3.22	3.10	2.29	2.31
Black-box	Unlearnable Training Music	-	4.03	4.45	3.98	4.12
	Generated Music (Trained on Unlearnable Music)	MuseGAN	2.44	3.78	1.94	2.88
		SymphonyNet	2.20	2.94	2.45	2.22
		MusicLM	3.41	3.04	2.78	2.34

https://mosis.eecs.utk.edu/harmonycloak.html

thanks