

### hosted by SBA Research Wien

Topic for today: CommentSense

Send us announcements & job openings!



#### Welcome by the Meetup organizers:



Thomas Lidy iGroove



René Donner mva.ai



Jan Schlüter JKU Linz



Alex Schindler AIT & TU Wien



Pavol Harar ISTA & ACALAI



### Welcome to SBA Research

Research Group Security & Privacy, Uni Wien

Rudolf Mayer & the MLDM Team





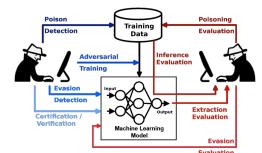
## Security & Privacy @ SBA & Uni Wien

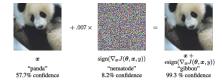


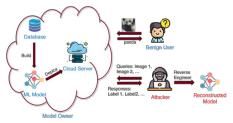
- -140 employees combined
- Scientific Lead: Edgar Weippl
- Research topics
  - Mathematics for Testing, Reliability and Information Security
  - Networks and Critical Infrastructures Security
  - Systems and (I)IoT Security
  - Decentralized Systems & Distributed Ledgers
  - Complexity and Resilience
- More details:
  - https://www.sba-research.org/research, https://sec.cs.univie.ac.at/

## Why do we host the Vienna Deep Learning Meetup?

- Machine Learning and Data Management Group
  - Privacy-preserving Machine Learning
    - Federated Learning, Synthetic Data, Differential Privacy, ...
  - Security of Machine Learning / Adversarial ML
    - Evasion attacks (adversarial examples), data poisoning, ...
  - Protection of ML assets
    - (Training) Data, models, outputs (e.g. genAl), ...
  - Machine Learning for security
    - Intrusion / malware / anomaly detection, ...









https://www.sba-research.org/mldm/



18:30 Welcome by the organizers
Welcome by our host: **SBA Research** 

18:45 CommentSense: An On-Device Al Browser Extension for Real-Time YouTube Comment Understanding

Marc Kroll

19:10 Hot Topics
Announcements

19:30 Networking & Discussions

# Hot Topics

Interesting recent research, feel free to contribute!



top papers from ISMIR 2025



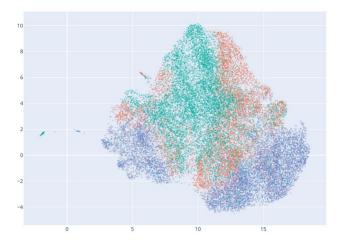
top papers from ISMIR 2025 some interesting ISMIR papers

## The Al Music Arms Race: On the Detection of Al-Generated Music

Laura Cros Vila, Bob Sturm, Luca Casini, David Dalmazzo

- collected 10k human-made, 10k suno, 10k udio songs
- computed general audio + CLAP features

#### 2D UMAP:

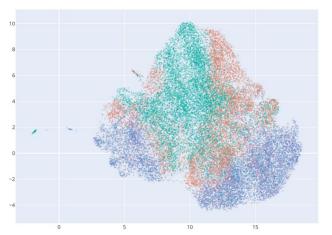


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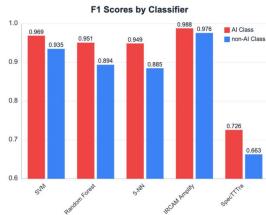
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#### 2D UMAP:



#### Classifier:

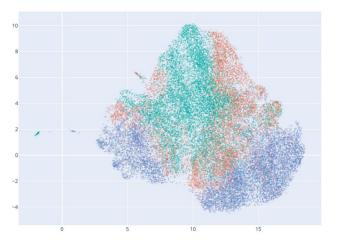


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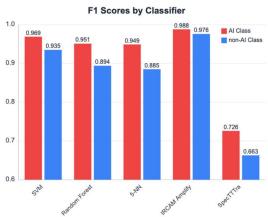
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#### But:

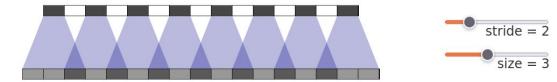
Performance breaks when downsampling audio to 22.05 kHz

Does not generalize to unseen services

IRCAM Amplify updates often – arms race

Darius Afchar, Gabriel Meseguer Brocal, Kamil Akesbi, Romain Hennequin

Neural audio codecs in music generation models use transposed strided convolutions

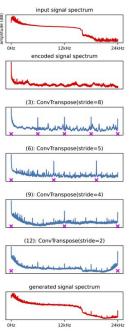


Transposed convolutions lead to <u>checkerboard artifacts in images</u>



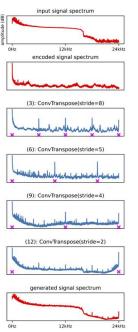
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Finding: Transposed convolutions lead to similar artifacts in spectra



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Idea: Train a linear regressor to differentiate original audio vs. output of neural audio codec, works on par with existing, more complex models

Class	Our	Reported from [17]
Real	99.87	99.7
Synthetic		
$\hookrightarrow$ DAC (14kbps)	99.68	99.3
$\hookrightarrow$ Encodec (24kbps)	99.81	99.7
→ Musika!	99.97	100.0

Class	Our	Reported from [16]
Real	99.97	99
Synthetic		
$\hookrightarrow$ Suno v3.5	100.00	100
$\hookrightarrow$ Suno $v3^{\dagger}$	100.00	96
$\hookrightarrow$ Suno $v2^{\dagger}$	99.90	78
$\hookrightarrow$ Udio 130	100.00	100
$\hookrightarrow Udio 32^{\dagger}$	39.83	96

Darius Afchar, Gabriel Meseguer Brocal, Kamil Akesbi, Romain Hennequin

Work done by Deezer

Fun facts:

up to 25% of music uploaded to Deezer is generated by Al

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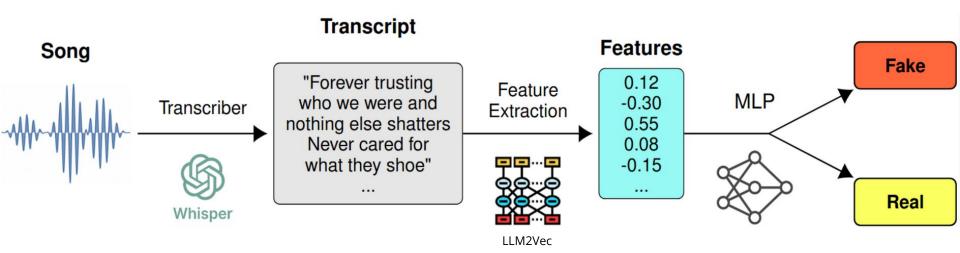
up to 25% of music uploaded to Deezer is generated by Al

up to 70% of streams of Al-generated music is by bots

## Al-Generated Song Detection via Lyrics Transcripts

Markus Frohmann, Elena Epure, Gabriel Meseguer Brocal, Markus Schedl, Romain Hennequin

Work done by Deezer with JKU Linz

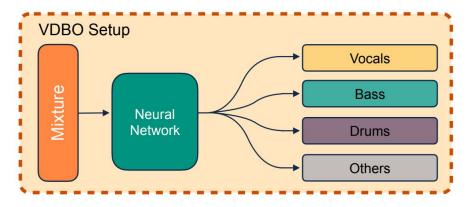


Somewhat worse than audio-based (90% vs. 97%), but generalizes across different services

### User-Guided Generative Source Separation.

Yutong Wen, Minje Kim, Paris Smaragdis

Off-the-shelf systems: four predefined stems (e.g., Spleeter, Demucs)



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VDBO Setup

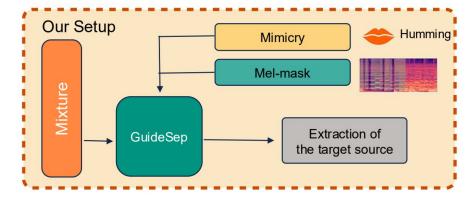
Vocals

Neural
Network

Drums

Others

Their system: select part to extract by mimicking it (humming, other instrument)



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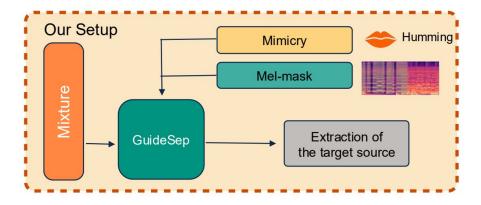
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Model: Conditioned diffusion U-Net

<u>Demo</u>:



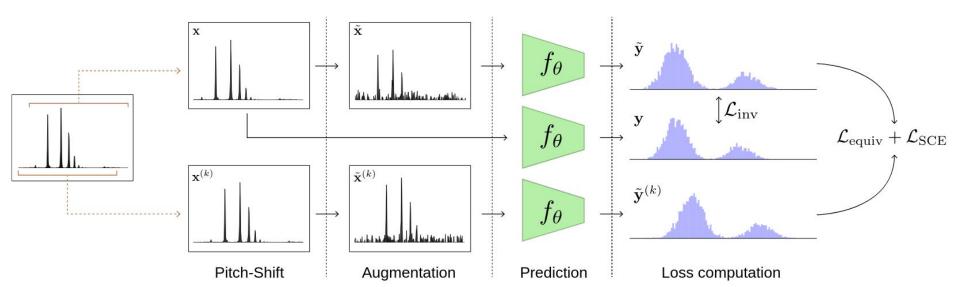




Data: Synthesized mimicry from audio-aligned MIDI

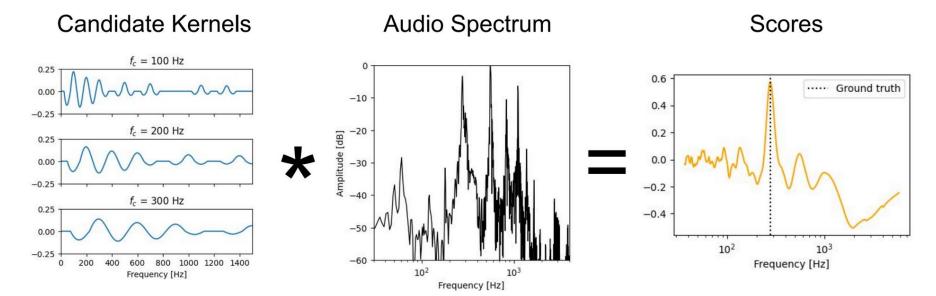
David Marttila, Joshua D. Reiss

PESTO: self-supervised deep learning approach for pitch estimation



David Marttila, Joshua D. Reiss

SWIPE: old spectral-candidate-based pitch estimation approach



David Marttila, Joshua D. Reiss

#### Findings:

Replacing audio frontend in PESTO with SWIPE improves results

	# params	Trained on	Raw Pitch Accuracy	
Method			MIR-1K	MDB-stem-synth
		MIR-1K	96.1%	94.6%
PESTO	28.9k	MDB-stem-synth	93.5%	95.5%
SWIPE-full	28.2k	MIR-1K	97.0%	89.7%
		MDB-stem-synth	96.1%	96.4%

David Marttila, Joshua D. Reiss

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Shrinking model from 28k parameters to 647 parameters further improves results

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SWIPE-full	28.2k	MDB-stem-synth	96.1%	96.4%
SWIPE-tiny	647	MIR-1K	96.6%	90.1%
		MDB-stem-synth	96.4%	96.5%

David Marttila, Joshua D. Reiss

#### Findings:

Replacing audio frontend in PESTO with SWIPE improves results

Shrinking model from 28k parameters to 647 parameters further improves results

SWIPE alone works almost as well → Performance was misreported in many pitch estimation papers

		Trained on	Raw Pitch Accuracy	
Method	# params		MIR-1K	MDB-stem-synth
SWIPE	-	-	96.2%	96.1%
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		MDB-stem-synth	96.4%	96.5%

### Announcements



Resources - all past talks & slides: github.com/vdlm

Send us SPEAKER suggestions, job & event announcements:



#### Call for Speakers!

Do you work on Deep Learning? In academia or industry?

We'd like to hear your story!

We are looking for speakers for **future meetups**.

**Short talks** (20-30 min) or **long talks** (40-60 min) welcome.

Talk to us in the break or send us an email!



#### Next Meetup:

October 23, 2025

Any suggestions for speakers or venues?

contact@vdlm.at

Send us SPEAKER suggestions, job & event announcements: