# Machine learning paradigms for music and audio understanding

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# Talk outline

1. Machine listening
2. Machine listening with limited data
3. Graph neural networks for audio
4. Self-supervised learning for machine listening
5. Multimodal learning for machine listening
6. Future perspectives

# Machine listening

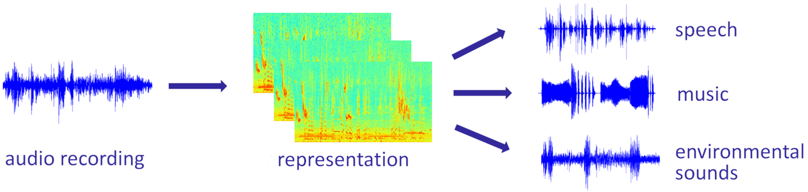
**Machine listening**

The ability of a machine to interpret and understand audio signals.

## Machine listening

The ability of a machine to interpret and understand audio signals.

- **Sounds**: speech, music, environmental/everyday sounds
- **Disciplines**: signal processing, machine learning, acoustics, perception

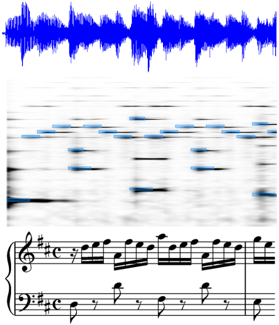


# Machine listening for music

Related to the field of **Music Information Retrieval (MIR)**

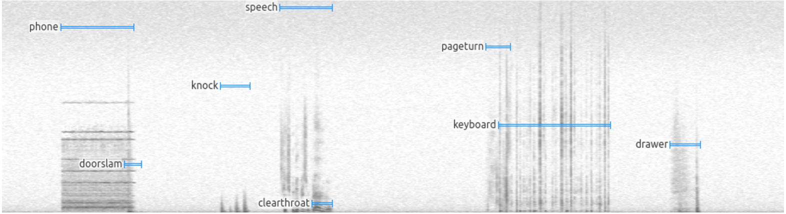
**Core problems**:

- Music tagging
- Music source separation
- Music transcription
- Audio identification
- & new multimodal music tasks



# Challenges in machine listening

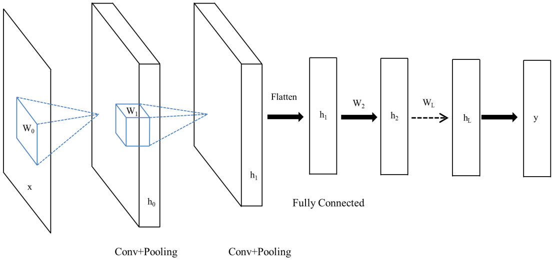
- Multiple overlapping sources
- Data scarcity
- Temporal dependencies
- Noise, distortions and effects
- Unseen domains
- Other modalities to aid audio understanding?



# Supervised learning for machine listening

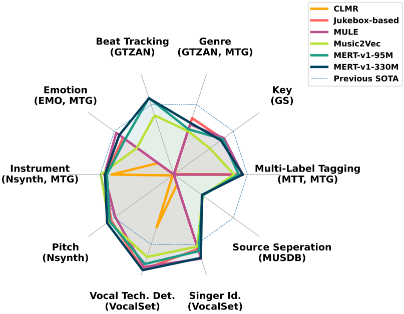
**Benchmark approaches** for machine listening tasks:

- Adopt a **supervised** deep learning approach
- Assume a sufficiently large, **strongly labelled** dataset
- Time-frequency representations or raw waveforms as **input**
- **Building blocks**: feedforward, convolutional & recurrent layers
- **Loss functions**: cross-entropy, MSE



# MARBLE benchmark

- **MARBLE**: an MIR benchmark, defining 18 tasks across four hierarchy levels, utilising 12 public datasets.
- **Task taxonomy**: score-level, performance-level, acoustic-level, high-level description
- Evaluation on several music audio pretrained models: MusiCNN, Jukebox, CLMR, Musicnet-ULarge, MAP-Music2Vec...




R. Yuan et al, "MARBLE: music audio representation benchmark for universal evaluation", in NeurIPS, 2023.

# Machine listening with limited data

# Domain adaptation for sound recognition

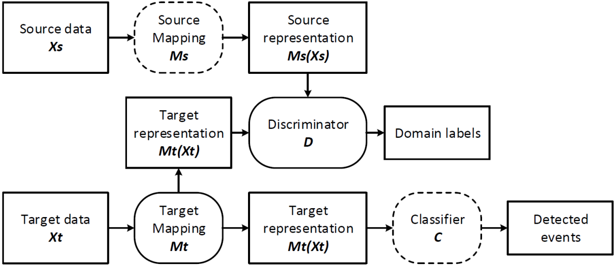
**Domain adaptation**

Sub-discipline of machine learning which deals with scenarios in which a model trained on a source distribution is used in the context of a different target distribution.

# Domain adaptation for sound recognition

## Domain adaptation

Sub-discipline of machine learning which deals with scenarios in which a model trained on a source distribution is used in the context of a different target distribution.

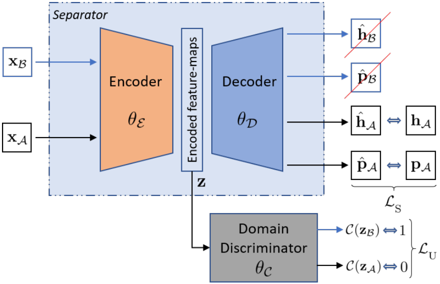



W. Wei, H. Zhu, E. Benetos, and Y. Wang, "A-CRNN: a domain adaptation model for sound event detection", in ICASSP, 2020.

# Domain adaptation for music source separation

Music source separation system able to adapt to unlabelled mixtures from a new domain.

Framework can be used with any architecture, number of sources, and input representation.





C. Lordelo, E. Benetos, S. Dixon, S. Ahlbäck, and P. Ohlsson, “Adversarial Unsupervised Domain Adaptation for Harmonic-Percussive Source Separation”, IEEE Signal Processing Letters, 28:81-85, 2021.

# Few-shot learning for audio classification

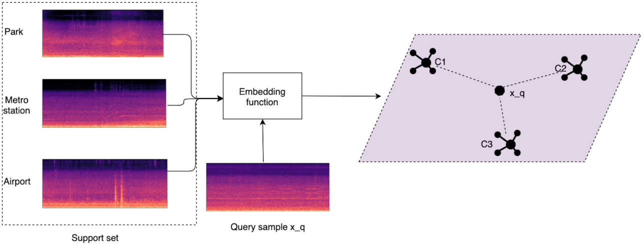
**Few-shot learning**

Learning from a limited number of labelled examples.

# Few-shot learning for audio classification

## Few-shot learning

Learning from a limited number of labelled examples.



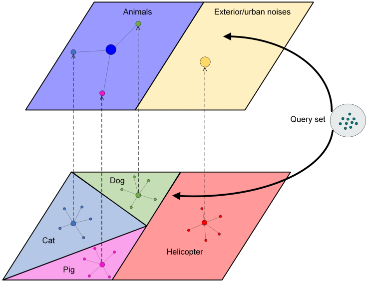

Each class prototype $c_k$ is the mean of the embedded support points $x_i$ belonging to its class: $c_k = \frac{1}{|S_k|} \sum_{(x_i) \in S_k} f_\phi(x_i)$

S. Singh, H. L. Bear, and E. Benetos, "Prototypical networks for domain adaptation in acoustic scene classification", in ICASSP, 2021.

# Few-shot learning for sound recognition

Proposing a **hierarchical prototypical network** to leverage knowledge rooted in audio taxonomies.

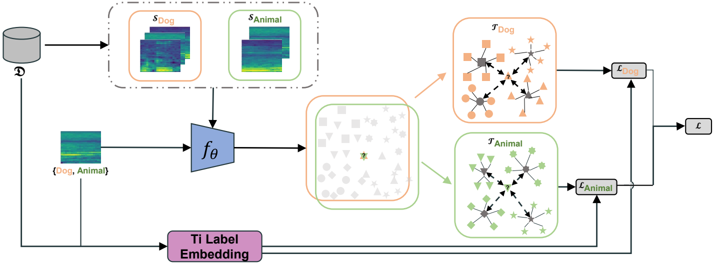
- Prototypes at the lower level: $c_k^{(0)} = \frac{1}{|S_k|} \sum_{(x_i) \in S_k} f_\phi(x_i)$
- Prototypes at a higher level $h$ in the taxonomy: $c_j^{(h)} = \frac{1}{|C_k^{(h)}|} \sum_{c_j^{(h)} \in C_j^{(h)}} c_j^{(h-1)}$




J. Liang, H. Phan, and E. Benetos, “Leveraging label hierarchies for few-shot everyday sound recognition”, in DCASE Workshop, 2022.

# Few-shot learning for sound recognition

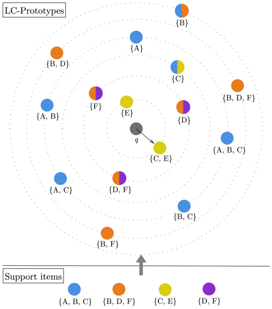
- Extending hierarchical prototypical networks to multi-label classification problems.
- Converts a multi-label classification problem to multiple single-label tasks & incorporates taxonomy knowledge in the training objective.




J. Liang, H. Phan, E. Benetos, "Learning from taxonomy: multi-label few-shot classification for everyday sound recognition", in ICASSP, 2024.

# Few-shot learning for world music

- Label-Combination Prototypical Networks (LC-Protonets) for multi-label few-shot learning
- LC-Protonets generate one prototype per label combination
- Applied to automatic audio tagging across diverse music datasets covering various cultures

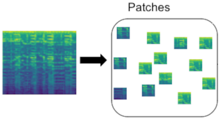



C. Papaioannou et al, “LC-Protonets: multi-label few-shot learning for world music audio tagging”, IEEE Open Journal of Signal Processing, 6:138-146, 2025.

# Graph neural networks for audio

# Graph neural networks for audio

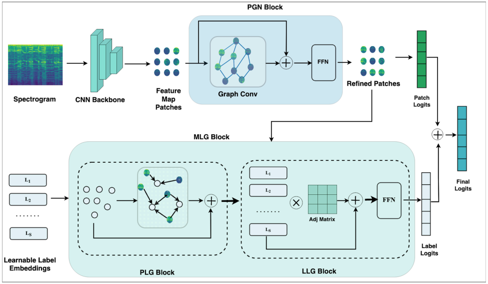
- Despite stacking multiple layers, the receptive field of convolutional layers remains severely limited.
- Attention mechanisms are able to map global context, but are not flexible enough to capture irregular audio objects.
- While effective, Transformers primarily cater to pairwise interactions and require substantial pretraining on large datasets
- Treating time-frequency representations as graph structures instead



# Graph neural networks for audio

ATGNN model converts spectrogram into a graph structure, and maps relationships between class features and corresponding spectrogram regions.

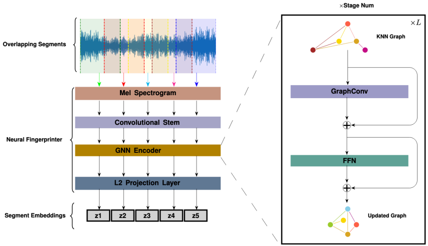
Comparable results with non-graph models, with significantly lower number of learnable parameters.




S. Singh, C. J. Steinmetz, E. Benetos, H. Phan, and D. Stowell, "ATGNN: audio tagging graph neural network", IEEE Signal Processing Letters, 2024.

# Graph neural networks for audio

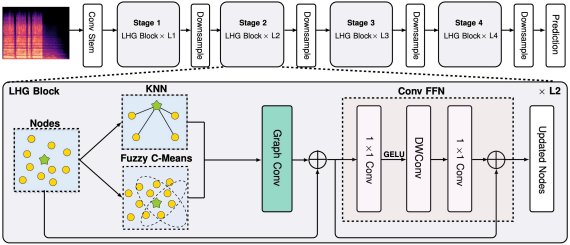
- Application of GNNs to audio identification
- Inspired from traditional audio fingerprinting approaches – spectrogram as constellation map of time-frequency points.
- Encoder constructs a k-NN graph from time-frequency representations and applies graph convolutions to encode local and global information




A. Bhattacharjee, S. Singh, and E. Benetos, "GraFPrint: a GNN-based approach for audio identification", in ICASSP, 2025.

# Graph neural networks for audio

- Local-Higher Order Graph Neural Network (LHGNN): integrate GNNs with clustering techniques
- k-NN learns local neighborhood relationships
- Fuzzy C-Means clustering enhances node attributes with clustering-based membership scores
- Nodes are updated using graph convolutions that encapsulate both local and extended node interactions



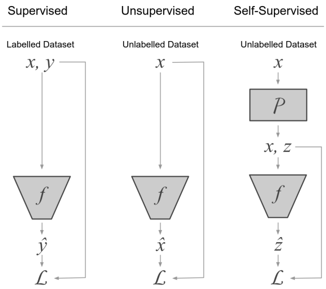

S. Singh, E. Benetos, H. Phan, and D. Stowell, ”LHGNN: local-higher order graph neural networks for audio classification and tagging”, in ICASSP, 2025.

# Self-supervised learning for machine listening

# Self-supervised learning

## Self-supervised learning

Special case of unsupervised learning, relying on pretext tasks that exploit knowledge about the data modality used for training.

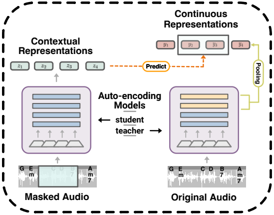


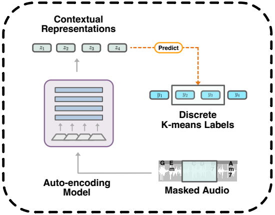

[Source: Ericsson et al, IEEE SPL 2022]

Common SSL approaches: transformation prediction, masked prediction, instance discrimination, and clustering

# Self-supervised learning for music

- Retraining speech SSL models (data2vec and HuBERT) on music data
- Pretraining on speech is helpful; pretraining on music is better; but models suffer on modelling polyphony and harmony
- Lack of music domain knowledge, lack of long-term sequence modelling

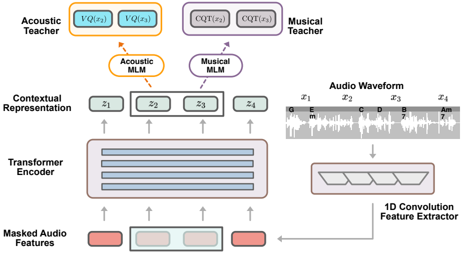



Y. Ma et al, “On the effectiveness of speech self-supervised learning for music”, in ISMIR, 2023.

# Self-supervised learning for music

- **MERT**: Music undERstanding model with large-scale self-supervised Training
- Multi-task paradigm to balance the acoustic and musical representation learning
- Overall architecture is similar to HuBERT, adapted to music: CQT reconstruction loss plus EnCodec (Défossez et al, 2022)

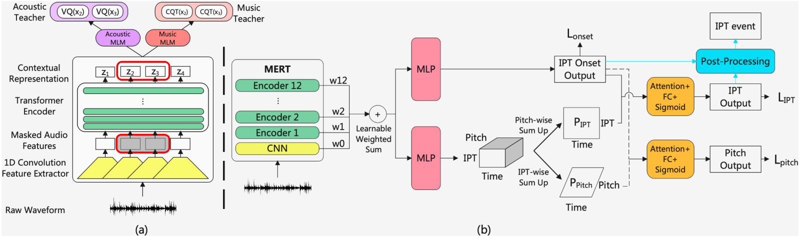



Y. Li et al, "MERT: acoustic music understanding model with large-scale self-supervised training", in ICLR, 2024.

# Self-supervised learning for music

- Model variant trained on publicly available data only (MERT-95M-public)
- Preliminary versions used k-means clustering with audio features: scaling issues
- Some capability in handling longer sequences, but still limited by the short 5-second training context
- Community impact: >750k downloads of MERT in Hugging Face (https://huggingface.co/collections/m-a-p)

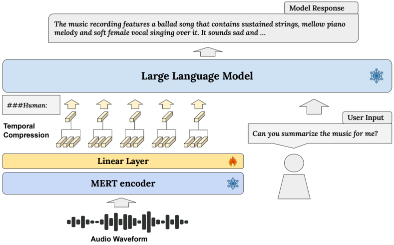
- Adapting MERT to a low-resource task: instrument playing technique (IPT) detection
- Pretraining on MERT, finetuning for IPT detection, pitch detection, and IPT onset detection




D. Li et al, "MERTech: instrument playing technique detection using self-supervised pretrained model with multi-task finetuning", in ICASSP, 2024.

# Self-supervised + multimodal learning for music

- **MusiLingo**: a system for music caption generation and music-related query responses.
- Aligning audio representations from MERT with the frozen Vicuna-7B language model
- New dataset of 60k music Q&A pairs

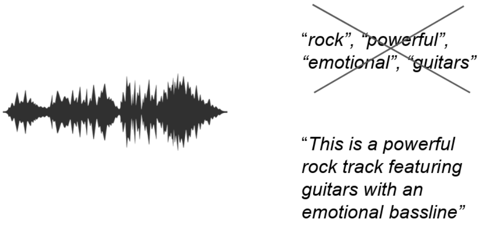



Z. Deng et al, "MusiLingo: bridging music and text with pre-trained language models for music captioning and query response", in NAACL, 2024.

# Multimodal learning for machine listening

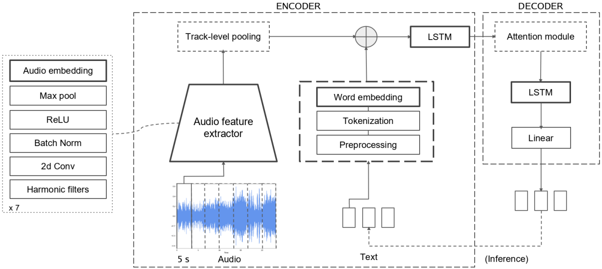
# From tags to natural language for audio description

- Audio description typically tackled with classification/regression tasks (e.g. tagging)
- Captioning provides more nuanced description, uses natural language and can be extended to new concepts
- Community activity on **automated audio captioning** as part of DCASE Challenge series



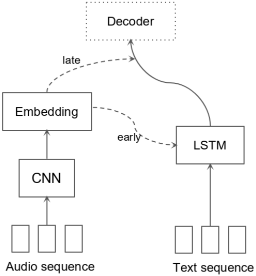
# MusCaps: generating captions for music audio

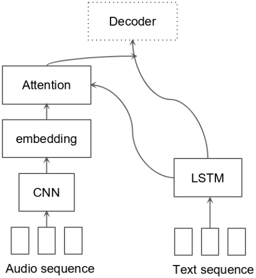
- First audio captioning model focussed on music
- Encoder-decoder network consisting of a multimodal CNN-LSTM encoder with temporal attention and an LSTM decoder




I. Manco, E. Benetos, E. Quinton and G. Fazekas, “MusCaps: generating captions for music audio”, in IJCNN, 2021.

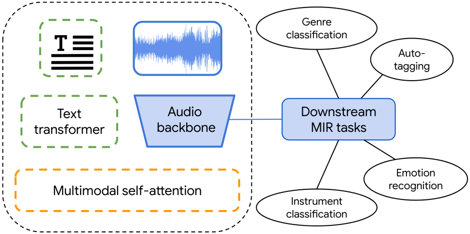
# MusCaps: modality fusion



# MuLaP: music and language pretraining

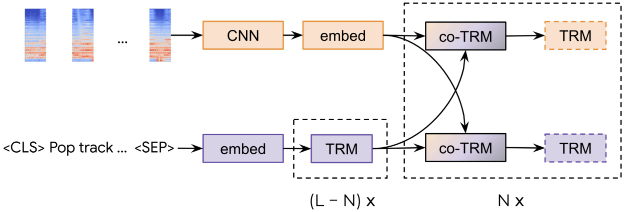
- MuLaP: leveraging weakly aligned natural language and audio to learn general-purpose music representations
- Can attain similar or better downstream performance when compared to traditional supervised techniques




I. Manco, E. Benetos, E. Quinton, G. Fazekas, “Learning music audio representations via weak language supervision”, in ICASSP, 2022.

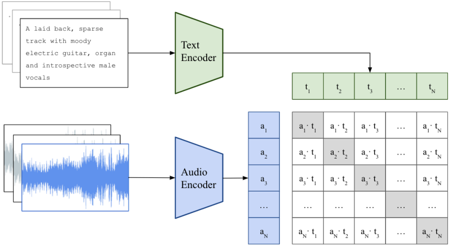
# MuLaP: music and language pretraining

- We design a multimodal Transformer made of two modality-specific branches (audio and text) and a co-attentional module
- We pre-train using three learning objectives: masked language modelling, masked audio modelling, audio-text matching



# MusCALL: contrastive audio-language learning for music

- Exploring multimodal contrastive learning for music audio language
- Applied to cross-modal retrieval for music, transferred to music classification tasks in a zero-shot setting




I. Manco, E. Benetos, G. Fazekas, and E. Quinton, "Contrastive audio-language learning for music", in ISMIR, 2022.

# MusCALL: failure cases

| Query Text | Text of the Top-1 Audio |
|---|---|
| *An atmospheric and introspective orchestral track featuring strings, piano, and synth.* | *An inspirational and moody orchestral track featuring strings and choir.* |
| *Deep chilled out space jazz with crisp beats and lush electronics.* | *Jaunty swing featuring trumpet.* |
| *Up tempo, pumping dance pop with female vocals.* | *Quirky, fun, positive disco party music.* |

In some "failure" cases, MusCALL still retrieves items that are semantically related to the query

# Song Describer Dataset

- **Song Describer dataset**: a new crowdsourced corpus of high-quality audio-caption pairs
- 1.1k human-written natural language descriptions of 706 music recordings, all publicly accessible and released under CC licenses

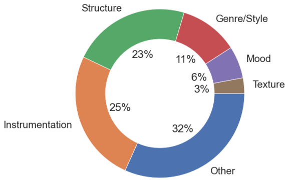
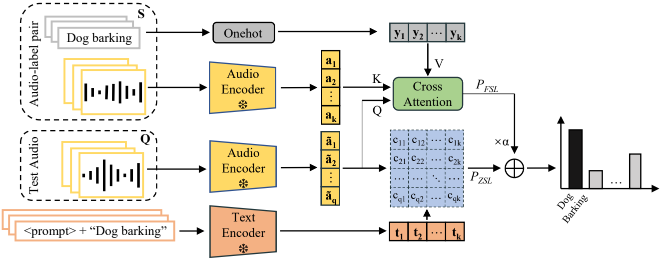



Figure: Distribution of music aspects by the most frequent word stems in the collected captions.

I. Manco et al, "The Song Describer Dataset: a corpus of audio captions for music-and-language evaluation", in NeurIPS ML4Audio Workshop, 2023.
https://github.com/mulab-mir/song-describer-dataset

# Audio-language models for few-shot learning

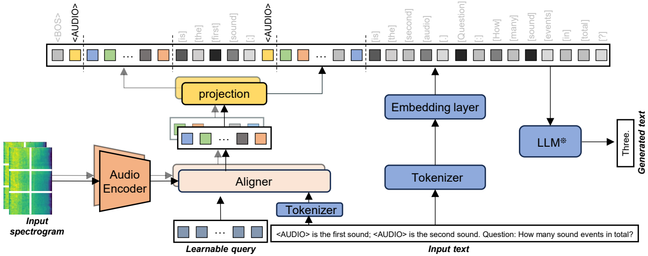
- Adapting contrastive audio-language models in low-shot scenarios is challenging
- Test embeddings attend to support embeddings and their corresponding one-hot labels




J. Liang et al, "Adapting language-audio models as few-Shot audio learners", in INTERSPEECH, 2023.

# Acoustic prompt tuning

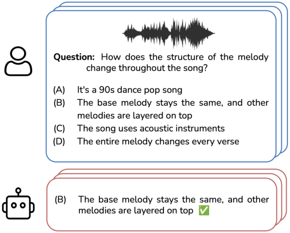
- Acoustic Prompt Tuning: a new adapter extending LLMs to the audio domain by injecting audio embeddings to the input of LLMs
- Capable of tackling diverse modelling tasks, such as few-shot audio classification and audio Q&A

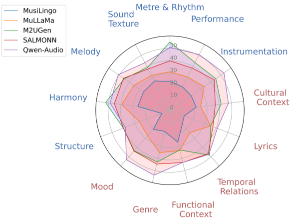



J. Liang et al, “Acoustic prompt tuning: empowering large language models with audition capabilities”, IEEE Transactions on Audio, Speech and Language Processing, 33:949-961, 2025.

# MuChoMusic Benchmark

- Benchmark for music understanding in audio-language models
- 1,187 multiple-choice questions about 644 music tracks
- Challenging and robust to unimodal shortcuts, exposes both audio and language hallucinations

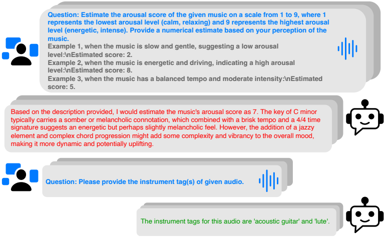



B. Weck et al, “MuChoMusic: Evaluating music understanding in multimodal audio-language models”, in ISMIR 2024. **Best paper award**
https://github.com/mulab-mir/muchomusic

# CMI-Bench

- CMI-Bench: reinterprets 14 core MIR tasks using an instruction-following format
- Scores open-ended outputs with standard metrics to compare fairly with supervised models
- Large performance gaps vs. supervised baselines
- Biases (culture, era, gender) emerge across tasks




Y. Ma, S. Li, J. Yu, E. Benetos, A. Maezawa, "CMI-Bench: a comprehensive benchmark for evaluating music instruction following", in ISMIR, 2025.

# Future perspectives

# Future perspectives

- Significant performance gaps between audio LLMs and supervised acoustic models
- Continual learning for audio and music
- Multimodal AI for acoustic and music understanding: beyond audio and text?
- Acoustic diversity & understanding low-resource corpora
- Resource-efficiency and sustainability

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