A Web Interface for Acoustic-Semantic Analysis of Extreme Metal Vocal Styles

Isabella Czedik-Eysenberg[1], Eric Smialek[2], Jan-Peter Herbst[2], Christoph Reuter[1]
[1]SInES, Department of Musicology, University of Vienna, Austria; [2]University of Huddersfield, United Kingdom

40. Jahrestagung der Deutschen Gesellschaft für Musikpsychologie (DGM), München, 7.-9. September 2024

This research was generously funded by EU Horizon / the Engineering and Physical Sciences Research Council (EPSRC) in the United Kingdom under grant EP/X02590X/1.

Background

Vocal styles in **extreme metal** involve expressive effects and techniques (e.g., *growling*, *screaming*, *shrieks*) that can serve as markers for different subgenres and convey specific **semantic qualities**. Particularly, **guttural vocals** in extreme metal are characterized by **low harmonicity** and **high roughness** and associated with expressive traits like "aggressiveness" (Tsai et al., 2010). Audio features can help classify metal vocals into broad style categories (Nieto, 2013; Kalbag & Lerch, 2022). Despite this awareness of vocal effects specific to individual subgenres, the **perceptual** organization of these styles has not yet been empirically demonstrated via participant responses and linked to relevant **audio features**.

Aims

We aim to explore extreme metal vocals through a semantically meaningful space of **verbal associations** and their correspondence with **audio features**. Based on this, **interactive web applications** are being developed that allows for the exploration of metal vocals in terms of their perception and acoustic properties.

Methods

We extracted short phrases from **115 professional metal vocal tracks** provided via a partnership with *Unstoppable Recording Machine*. These excerpts were used in perceptual experiments and analyzed acoustically by extracting audio features using `PRAAT/Parselmouth` (Boersma, 2001; Jadoul et al., 2018), `Librosa` (McFee et al., 2015), and `Essentia` (Bogdanov et al., 2013).

Experiment 1: Similarity Rating

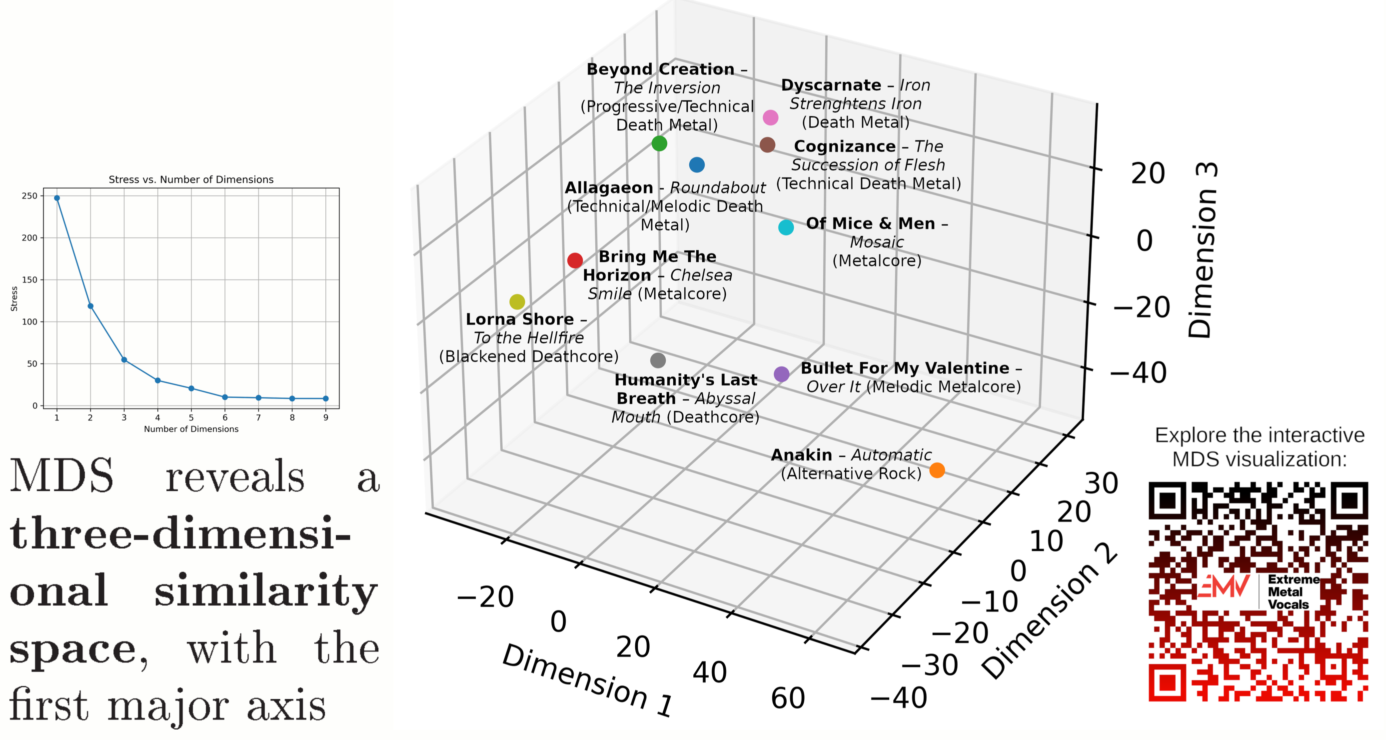
To identify the main **perceptual dimensions** of different metal vocal styles, 14 subjects rated a subset of 10 excerpts on a slider for **pairwise similarity** (45 comparisons). The mean similarity matrix forms the basis for a perceptual similarity space computed using **multidimensional scaling** (MDS).

Experiment 2: Verbal Associations

In a second experiment, vocal excerpts were played to participants across the entire dataset on a self-developed web platform to collect **verbal descriptions** of the vocals.
Participants responded both by typing **free associations** and using **preselected tags**.

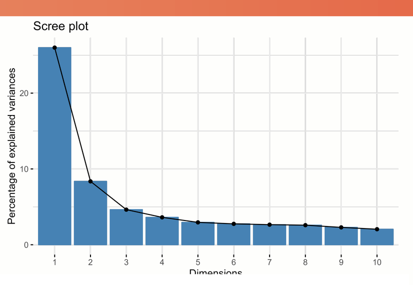
67 people participated in the task, providing 6,073 descriptive adjectives in total (4,493 tags and 1,580 free associations).

Similarity Space

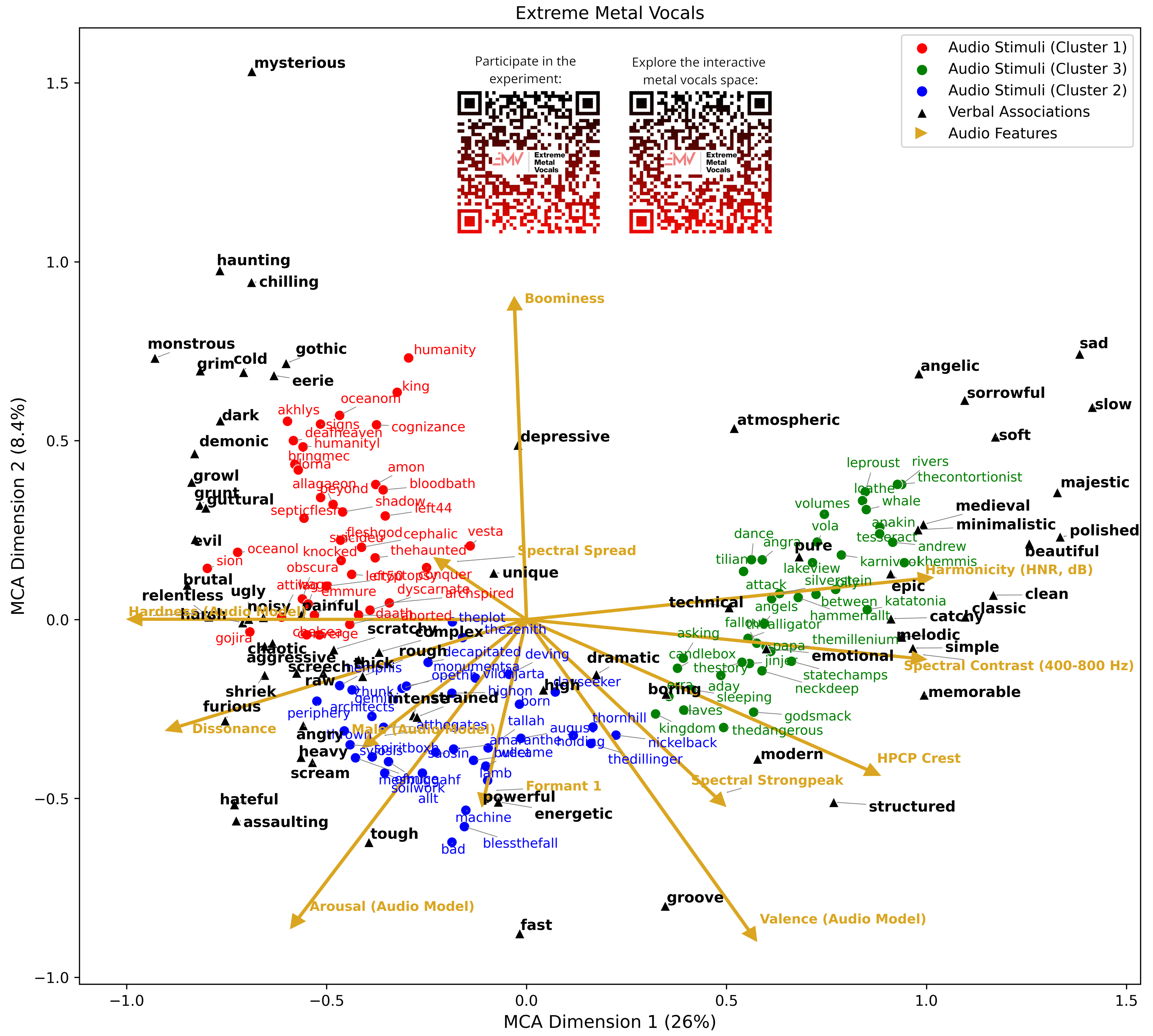


MDS reveals a **three-dimensional similarity space**, with the first major axis contrasting **harmonic** vs. **inharmonic** vocals (*Harmonic-to-Noise Ratio* (HNR): $r = 0.837$, $p = 0.005$; *Spectral Complexity*: $r = -0.959$, $p < 0.001$).
The second perceptual dimension shows no linear correlations with extracted sound features, while the third dimension is related to the position of the higher **formants** (e.g., $F2$: $r = -0.855$, $p = 0.003$).

Multiple Correspondence Analysis of Verbal Tags



Starting with the **4,493 selected tags**, we conducted a **multiple correspondence analysis** (MCA) based on whether particular tags occurred for particular stimuli. We opted for a two-dimensional configuration, with the first dimension explaining 26% of the variance and the second dimension explaining 8.4%.



Acoustically, the **first dimension** of descriptions according to the MCA, shows a very strong correlation with *Harmonic-to-Noise Ratio* (HNR) and other related descriptors referring to aspects of **inharmonicity**, **noisiness**, and **roughness** (see table).

Dimension 1

Audio Feature	r	p
Harmonic-to-Noise Ratio	0.932	<0.001
Shimmer	-0.929	<0.001
Spectral Contrast (400-800 Hz)	0.916	<0.001
Sensory Dissonance	-0.825	<0.001

Dimension 2

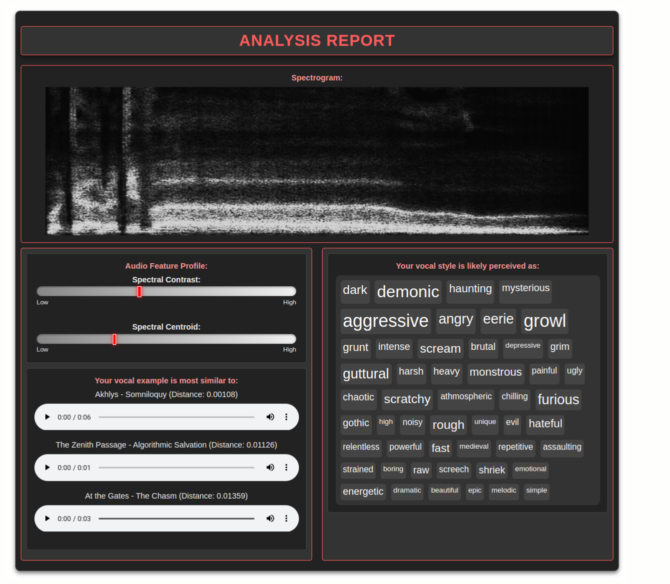
Audio Feature	r	p
Valence (Model)	-0.468	<0.001
Arousal (Model)	-0.449	<0.001
Timbral Boominess	0.467	<0.001
Formant 1	-0.263	0.004

The **second dimension** of the MCA, however, demonstrates a much less clear relationship with audio features (see table). The strongest relations are found with audio models for predicting perceived **valence** and **arousal**. It is characterized by a contrast between two groups of associations: *fast/groove/tough/energetic/assaulting* vs. *mysterious/haunting/chilling/angelic/atmospheric*.

Conclusion and Web Applications

The different analytical approaches all indicate that **harmonicity** is the most important perceptual axis for evaluating different styles of metal vocals. **Comparing** the results of the **two experiments**, it can be found that not only the first MCA dimension significantly correlates with the respective MDS dimension ($r = 0.901$, $p < 0.001$), but also the second MCA dimension corresponds to the (inverted) second dimension of the MDS relatively well ($r = -0.813$, $p = 0.004$). While demonstrating a less clear relationship with audio features, this second dimension may represent a broad dichotomy of aesthetic tropes related to ***"quotidian human toughness"*** vs. the **supernatural**.
Smialek (2023) argues that this distinction sets apart traditional metal genres from more controversial, newer forms like metalcore.

Our findings can be **explored interactively** through a **web application**, allowing users to experience them both aurally and visually. An additional application is being developed, which allows analysis of **self-uploaded vocal examples**, which we hope can serve as a helpful resource for vocalists training and evaluating their performance of expressive vocal styles.



References

Bogdanov, D., Wack, N., Gómez Gutiérrez, E., Gulati, S., Boyer, H., Mayor, O., Roma, G., Salamon, J., Zapata, J. & Serra, X. (2013). Essentia: An audio analysis library for music information retrieval. In *14th Conference of the International Society for Music Information Retrieval (ISMIR)*, pp. 493–8. | **Boersma, P. (2001).** PRAAT, a system for doing phonetics by computer. *Glot International, 5*, 341–345. | **Jadoul, Y., Thompson, B., & De Boer, B. (2018).** Introducing Parselmouth: A Python interface to praat. *Journal of Phonetics, 71*, 1–15. | **Kalbag, V., & Lerch, A. (2022).** Scream detection in heavy metal music. *arXiv preprint* arXiv:2205.05580. | **McFee, B., Raffel, C., Liang, D., Ellis, D. P., McVicar, M., Battenberg, E. & Nieto, O. (2015).** librosa: Audio and music signal analysis in python. *Proceedings of the 14th python in science conference* (Vol. 8, 18–25). | **Nieto, O. (2013).** Unsupervised clustering of extreme vocal effects. In *Proc. 10th Int. Conf. Advances in Quantitative Laryngology* (p. 115–116). | **Smialek, E. (2023).** Contempt-of-Core: A Reception History of Metalcore Subgenres as Abject Genres. In J.-P. Herbst (Ed.), *The Cambridge Companion to Metal Music* (pp. 281–298). Cambridge University Press. | **Tsai, C. G., Wang, L. C., Wang, S. F., Shau, Y. W., Hsiao, T. Y., & Auhagen, W. (2010).** Aggressiveness of the growl-like timbre: Acoustic characteristics, musical implications, and biomechanical mechanisms. *Music Perception, 27(3)*, 209–222.