Correlations Between Text Topics and Music Dimensions in Metal Music Using Latent Dirichlet Allocation and High-Level Audio Features

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Background

As **audio** and **text** features provide complementary layers of information on songs, a combination of both data types has been shown to improve automatic classification of high-level attributes in music such as genre, mood and emotion (Neumayer and Rauber, 2007; Laurier et al., 2008; Hu and Downie, 2010; Kim, 2010). Multimodal approaches interlinking these features offer insights into possible relations between lyrical and musical information (see Nichols et al., 2009, McVicar et al., 2011; Yu et al. 2019).

Therefore, we examine the connection between audio features and the lyrical content of metal music by combining **automated extraction** of **high-level music properties** and **quantitative text analysis** on a large corpus of music from this genre.

Sound dimensions like loudness, distortion and particularly "*hardness*"/"heaviness" play an essential role in defining the sound of metal music (Reyes, 2008; Mynett, 2013; Herbst, 2017). **Topics** typically ascribed to metal lyrics contain *sadness*, *death*, *freedom*, *nature*, *occultism* or *unpleasant/disgusting objects* and are often labeled as *brutal*, *dystopian* or *satanistic* (Podoshen et al., 2014; Bayer, 2016; Cheung and Feng, 2019).

Aim

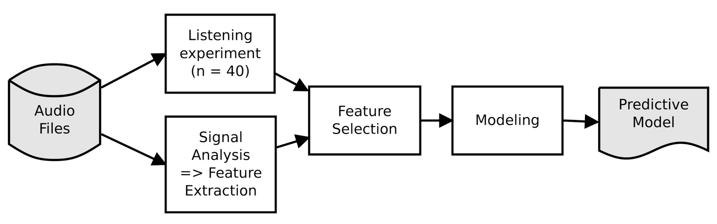
By combining audio feature extraction and text analysis, we:

1. offer a comprehensive overview of the **lyrical topics** present within the metal genre
2. are able to address whether or not **music dimensions** like *hardness* and *darkness* are associated with the occurrence of brutal (and other) textual topics.

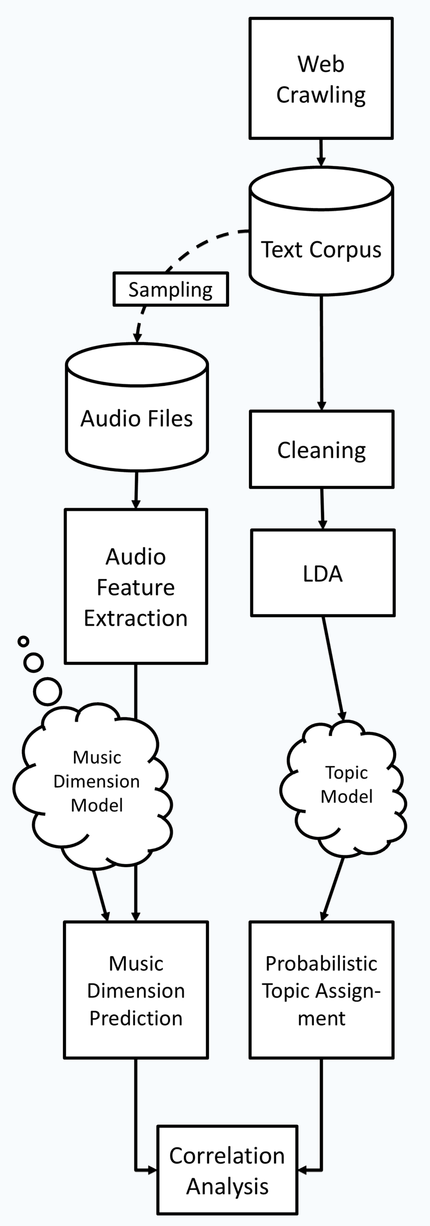
Method

Audio Feature Models

This research builds on a previous music perception study (Czedik-Eysenberg, 2018): Ratings on attributes like *hardness* and *darkness* were obtained for 212 music stimuli by 40 raters each. Based on this, **prediction models** for the automatic extraction of high-level audio feature dimensions were trained via **machine learning** methods.



Models embedded features implemented in:
- *LibROSA* (McFee et al. 2015)
- *Essentia* (Bogdanov et al. 2013)
- *timbral models* developed as part of the *AudioCommons* project (Pearce et al. 2013)



Web Crawling & Topic Models

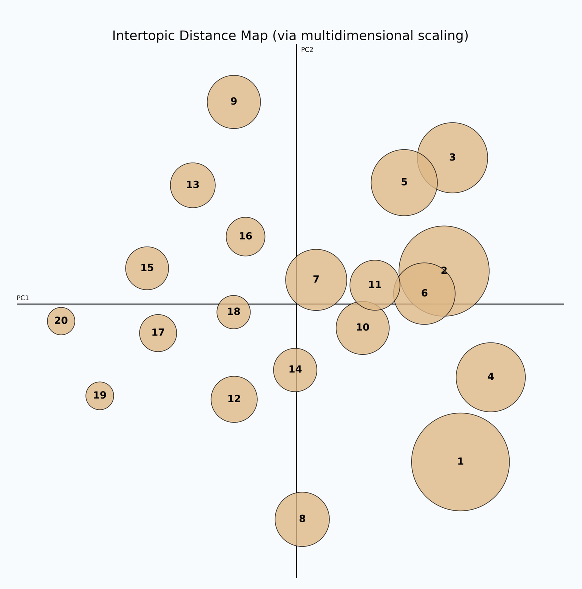
We programmed a **web crawler** to automatically retrieve metal song lyrics from *www.darklyrics.com*. After **cleaning procedures** (restricting language to English, removing stopwords, stemming), our subsample included 124.288 texts.

We applied **latent Dirichlet allocation** (LDA, Blei et al., 2003) on the remaining subsample to construct a probabilistic **topic model**. Log-Perplexity and Log-U-Mass Coherence were used as goodness of fit-measures and the resulting models analyzed qualitatively. For the purpose of interpretability, a topic model including 20 topics was chosen. The most salient and typical words for each topic were examined.

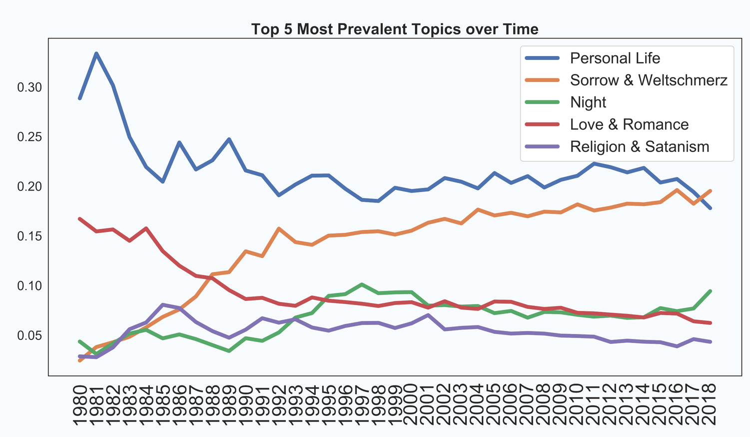
Finally, we drew a sample of 503 songs and used Spearman's ρ to identify correlations between the topics retrieved and the audio feature dimensions obtained by the high-level audio feature models. Bonferroni correction was applied in order to account for multiple-testing.

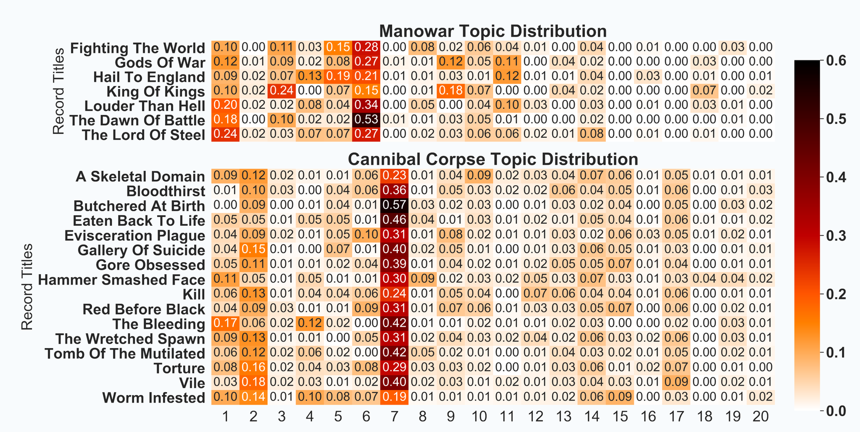
Results & Conclusions

Topic	Interpretation	Salient Terms (Top 10)	Darkness ρ	Hardness ρ
1	Personal Life	know, never, time, see, way, take, life, feel, make, say	-0.195**	-0.262**
2	Sorrow & Weltschmerz	life, soul, pain, fear, mind, eye, lie, insid, lost, end	0.042	-0.002
3	Night	dark, light, night, sky, sun, shadow, star, black, moon, cold	-0.082	-0.098*
4	Love & Romance	night, eye, love, like, heart, feel, hand, run, see, come	-0.196**	-0.273**
5	Religion & Satanism	god, hell, burn, evil, soul, lord, blood, death, satan, demon	0.11*	0.164**
6	Battle	fight, metal, fire, stand, power, battl, steel, sword, burn, march	0.158**	0.159**
7	Brutal Death	blood, death, dead, flesh, bodi, bone, skin, cut, rot, rip	0.176**	0.267**
8	Vulgarity	fuck, yeah, gon, like, shit, littl, head, girl, babi, hey	0.075	0.056
9	Archaisms & Occultism	shall, upon, thi, flesh, thee, behold, forth, death, serpent, thou	0.115*	0.175**
10	Epic Tale	world, time, day, new, end, life, year, live, last, earth	0.013	0.018
11	Landscape & Journey	land, wind, fli, water, came, sky, river, high, ride, mountain	-0.067	-0.125*
12	Struggle for Freedom	control, power, freedom, law, nation, rule, system, work, peopl, slave	0.095*	0.076
13	Metaphysics	form, space, exist, beyond, within, knowledg, shape, mind, circl, sorc	0.066	0.064
14	Domestic Violence	kill, mother, children, pay, child, live, anoth, father, name, innoc	0.060	0.070
15	Dystopia	human, race, disease, breed, destruct, machin, mass, seed, destroy, earth	0.191**	0.240**
16	Mourning Rituals	ash, word, dust, stone, speak, weep, smoke, breath, tongu, funer	0.031	0.015
17	(Psychological) Madness	mind, twist, brain, mad, self, half, mental, terror, urg, obsess	0.153*	0.107*
18	Royal Feast	king, rain, drink, fall, crown, sun, rise, bear, wine, color	-0.046	-0.031
19	Rock'n'Roll Lifestyle	rock, roll, train, addict, explod, wreck, shock, chip, leagu, raw	0.032	0.038
20	Disgusting Things	anim, weed, ill, fed, maggot, origin, worm, incest, object, thief	0.075	0.064

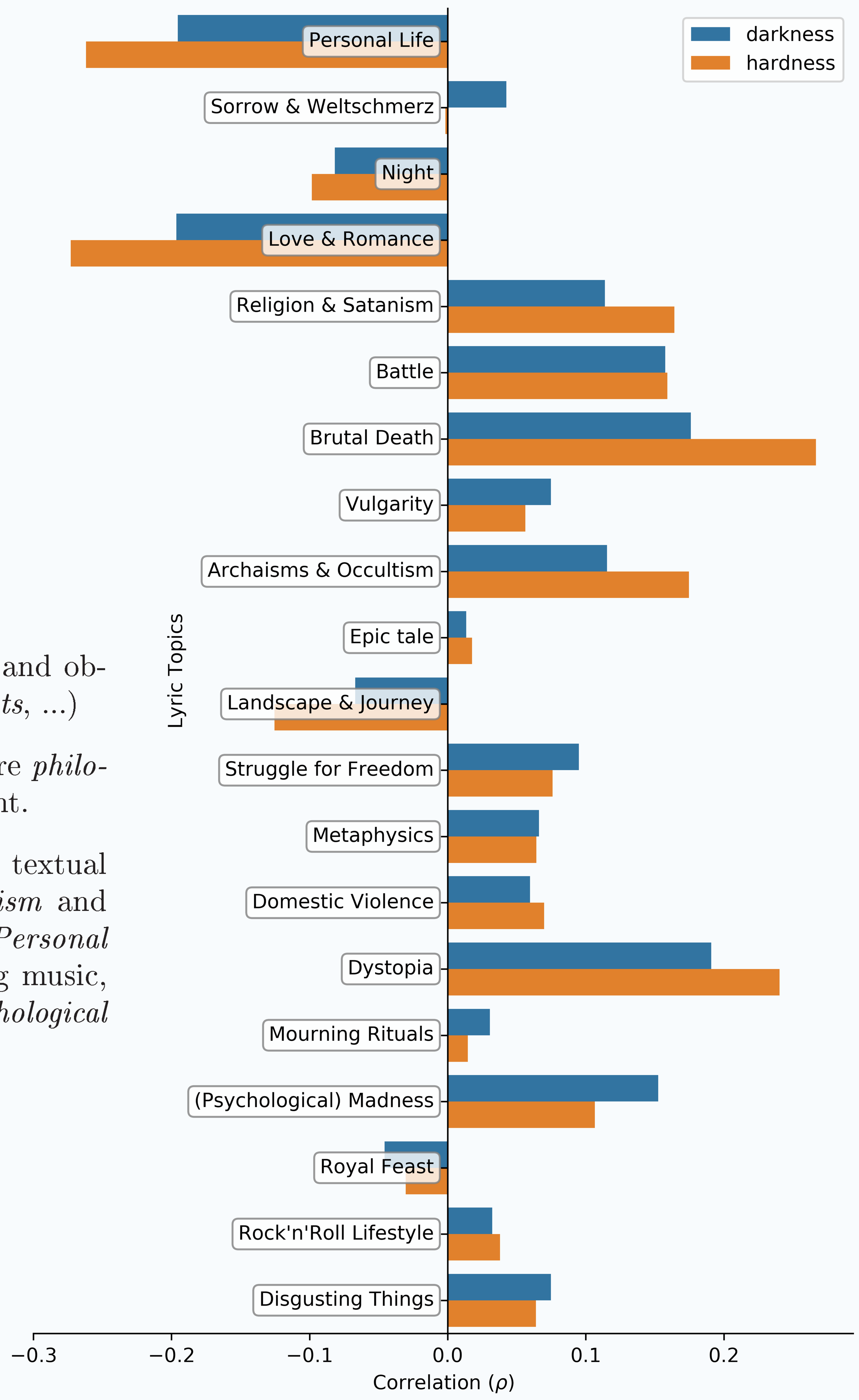


- Typical **text topics** identified in qualitative analyses could be confirmed and objectified using a large text corpus (e.g. *Satanism*, *dystopia*, *disgusting objects*, ...)
- Within the topic configuration, a **latent dimension** can be identified where *philosophical* and *brutal* topics oppose texts with more *mundane/shallow* content.
- It could be shown that musical **hardness** is particularly associated with textual themes of *Brutal Death*, *Dystopia*, *Archaisms*, *Occultism*, *Religion/Satanism* and *Battle*, while it is negatively linked to rather mundane topics concerning *Personal Life* and *Love & Romance*. The same is true for **dark/gloomy** sounding music, which in turn is specifically related to themes such as *Dystopia* and *Psychological Madness*.





⇒ In the **future**, it is planned to extend the investigations into the general connections between audio feature dimensions and textual themes to a comprehensive corpus of music from **different genres**.



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