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Semantic Analysis of Music Discourse

Predicting a Song's Emotive Qualities Based on Online Commentary

NCUR 2021

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Oregon State University – Cascades

College of Engineering – School of EECS

Introduction

- **Goal**: Determine emotional affect of music directly from social media commentary
- Existing methods are expensive, time consuming
- Discussions on social media platforms can be analyzed for their semantics and sentiment

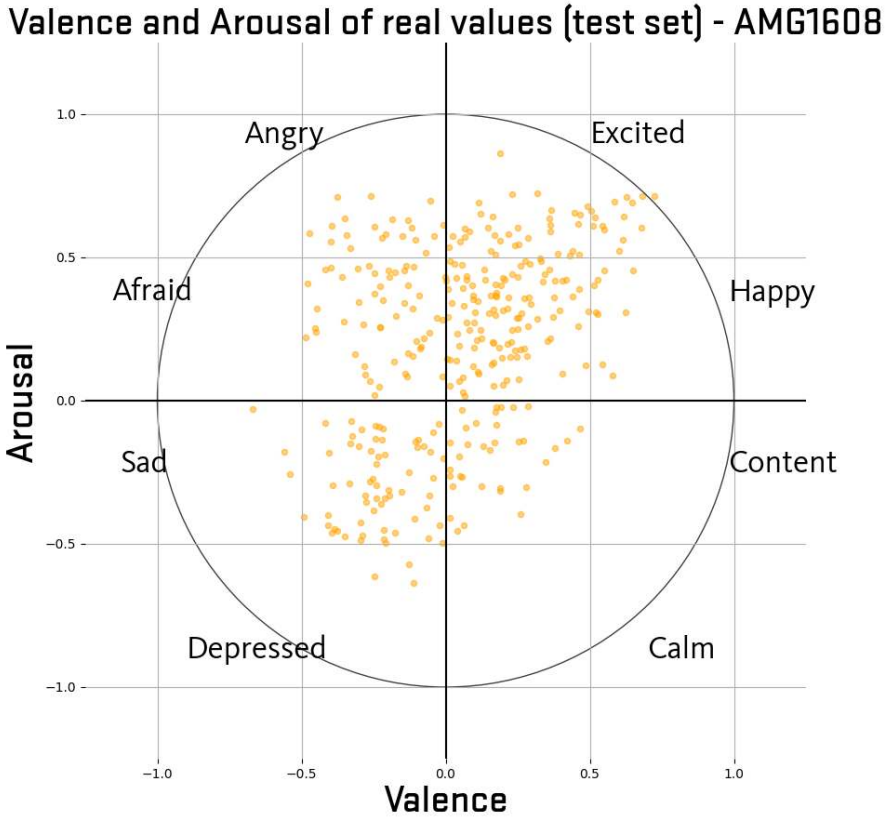

Figure 1 – The AMG-1608 valence and arousal labels visualized with a circumplex model.

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Experiment

- Scrape comments from Reddit
- Compare discourse against semantic wordlists
- Build features from aggregations
- Predict valence & arousal of song

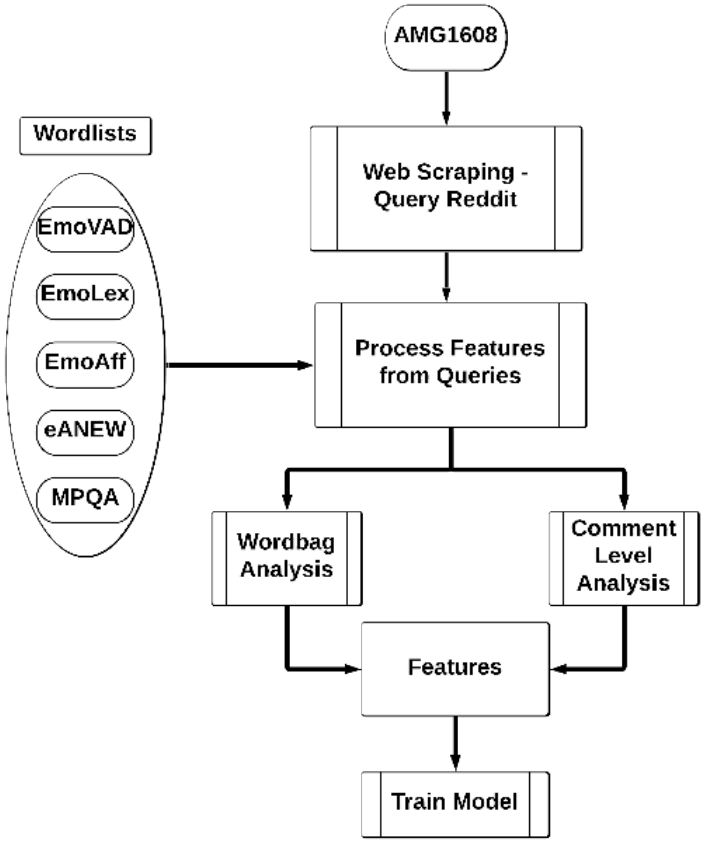

Figure 2 – A flowchart demonstrating how we predict song valence/arousal from a given set of songs.

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Song Dataset – AMG1608

- Songs from All Music Guide
- *n* = 1608
- 665 annotators
- Rated by valence, arousal [5]



Figure 3 – The graphical user interface used by annotators of the AMG1608 dataset [5]

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Song Dataset – Deezer

- Selections from Million Song Dataset, Deezer API
- Synthetic valence/arousal
  - Using audio and lyric features [8]
- *n = 18,644*

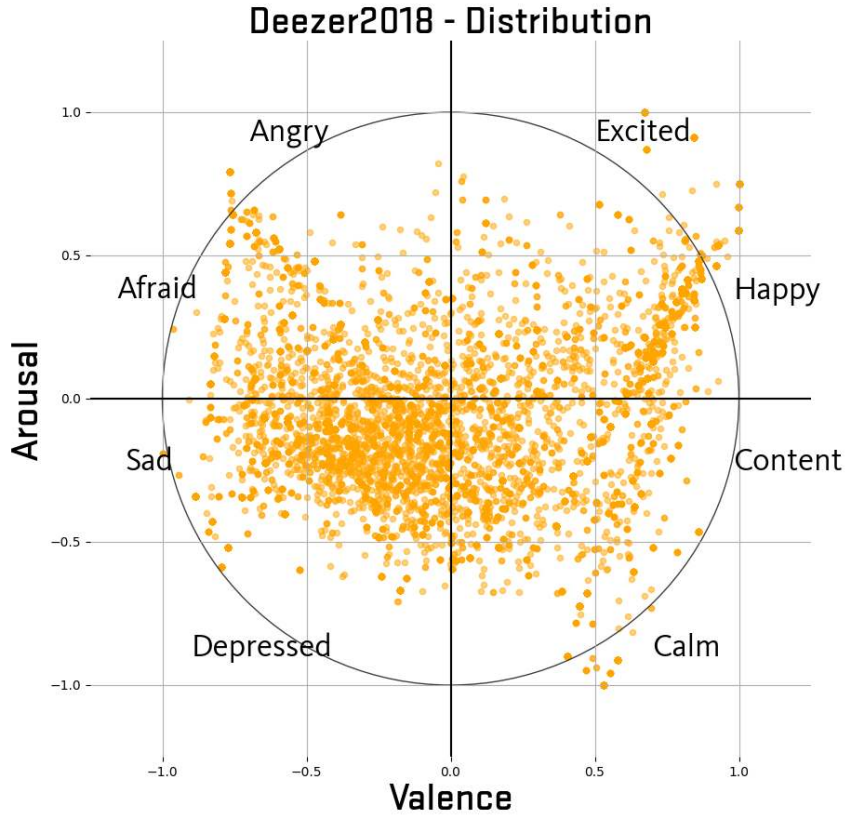

Figure 4 – A circumplex model representing the Deezer 2018 valence and arousal annotations [8]

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Word Datasets

- Manually annotated, single-word lists
- Extended ANEW
  - Valence, arousal dominance annotations[7][1]
- MPQA
  - Positive, negative, neutral sentiment[6]

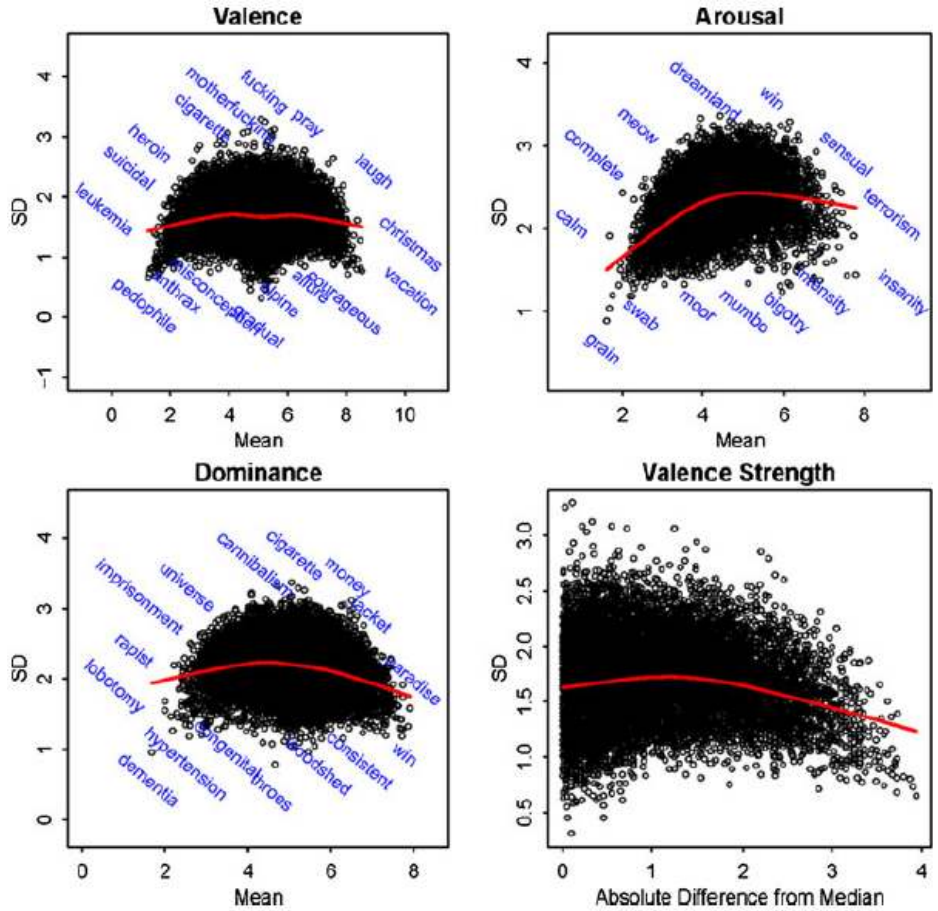

Figure 5 – Standard deviations of V/A/D ratings from the Extended ANEW dataset [1]

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Word Datasets [cont]

- NRC Semantic Wordlists:
  - EmoVAD
    - Valence, Arousal, Dominance[2]
  - EmoAff
    - Affect Intensity[3]
  - EmoLex
    - Affect presence[4]

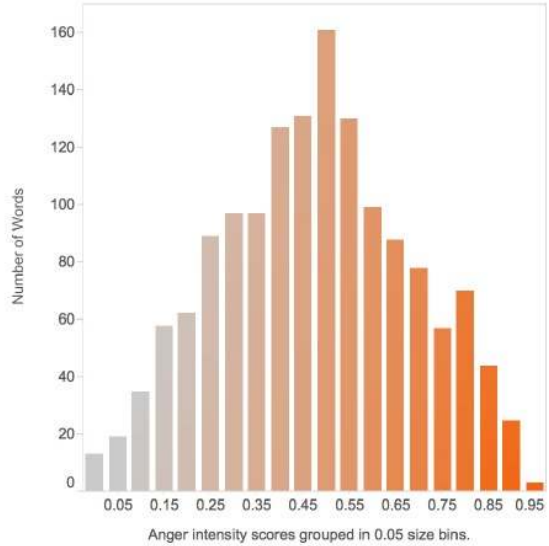

Figure 6 – A histogram of word-anger intensities in the EmoAff dataset [3]



Figure 7 – A visualization of the number of words which were associated with an affect in the EmoLex dataset [4]

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Method

1. Pull comments from Reddit
2. Comment analysis
   - Wordbag
   - Comment level
3. Generate features
   - Valence, arousal, dominance
   - Positive/negative sentiment
   - Affect presence/intensity

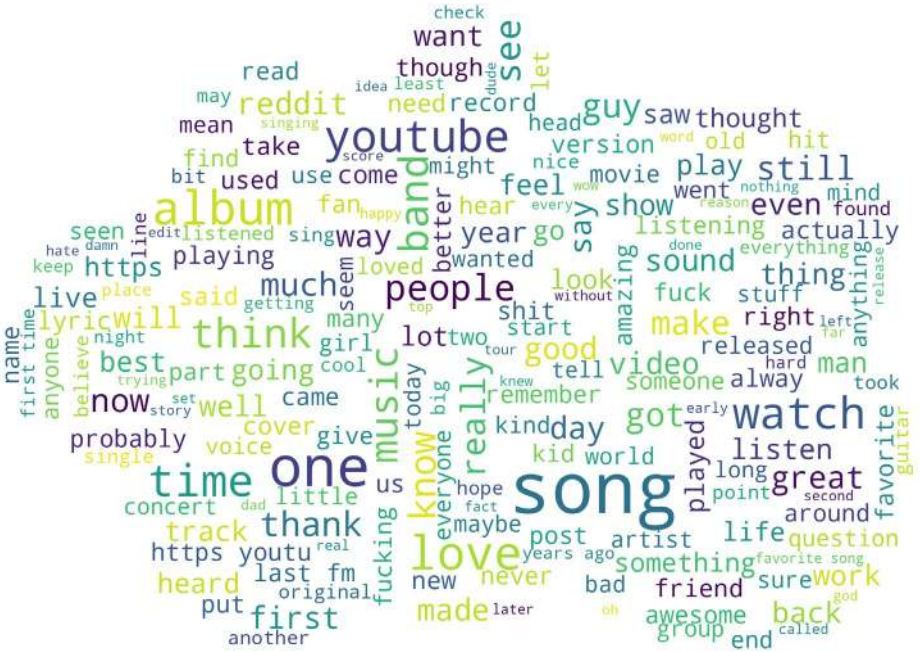

Figure 8: A wordcloud representing the frequency of words pulled from reddit queries based on the AMG1608 dataset

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Results – Comment Stats

Metric	Deezer	AMG1608
Total Comments	744,999	148,032
Mean Comments	61.25 ± 245.65	105.66 ± 441.79
Median Comments	10	22
Mean Comment Len.	54.01 ± 107.23	49.03 ± 81.19
Median Comment Len.	26	27
Yield	64.17%	87.13%

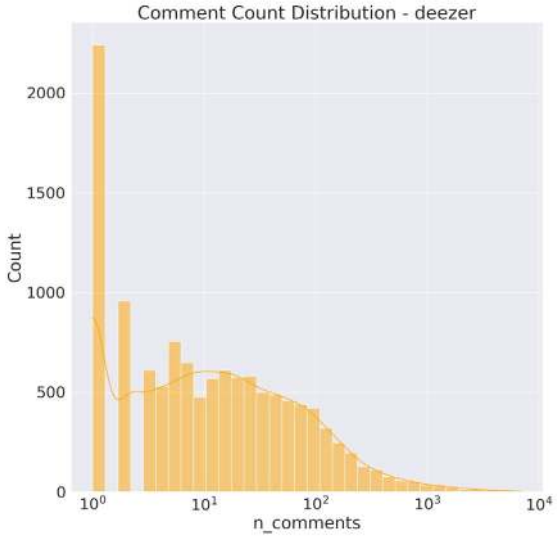
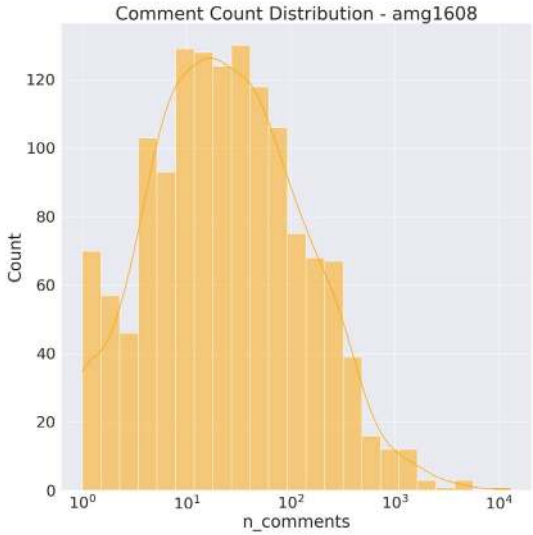


Figure 9, 10: Distribution charts for the number of comments in Deezer and AMG1608 based reddit queries



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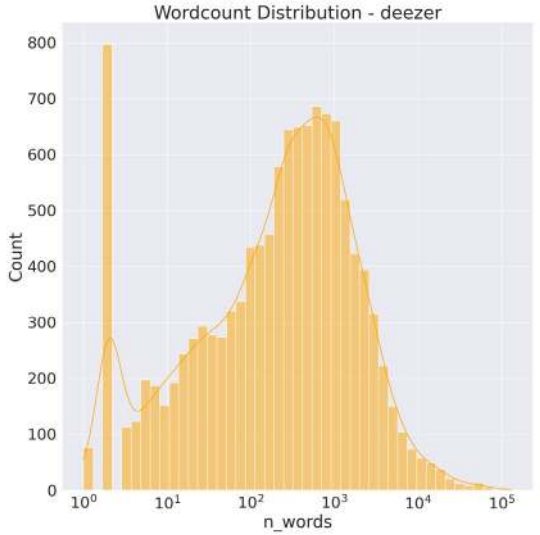
Results – Word Stats

- Deezer – left-shifted, low yield
- AMG – Even distribution



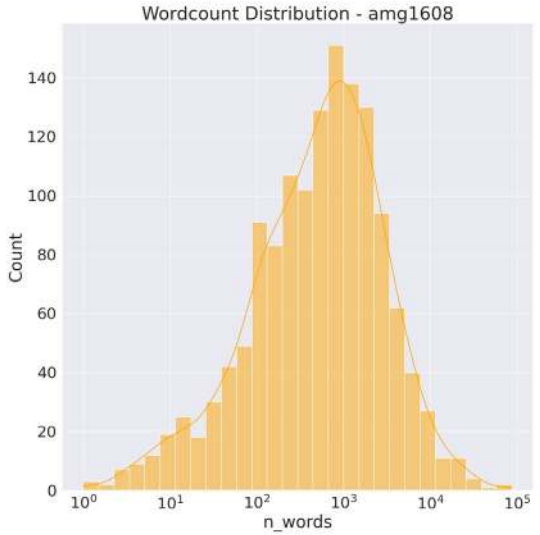


Figure 11, 12: Distribution charts for the number of words in Deezer and AMG1608 based reddit queries

Metric	Deezer	AMG1608
Total Words	13,778,033	2,438,423
Mean Wordcount	1133.34	1742.98
Wordcount Stdev.	3953.09	4631.29
Median Wordcount	277	609

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Results – Feature Selection

- Valence, Arousal Features
- BsmVAD, EmoVAD
- Strong correlations

Index	Feature Name	Correlation
1	EmoVAD_glob_a_mean	0.0220
2	EmoVAD_glob_a_uniq_mean	0.0174
4	EmoVAD_glob_a_uniq_std	0.0124
6	EmoVAD_glob_v_mean	0.0078
8	BsmVAD_glob_a_uniq_mean	0.0061
24	EmoVAD_v_uniq_stds_mean	0.0028

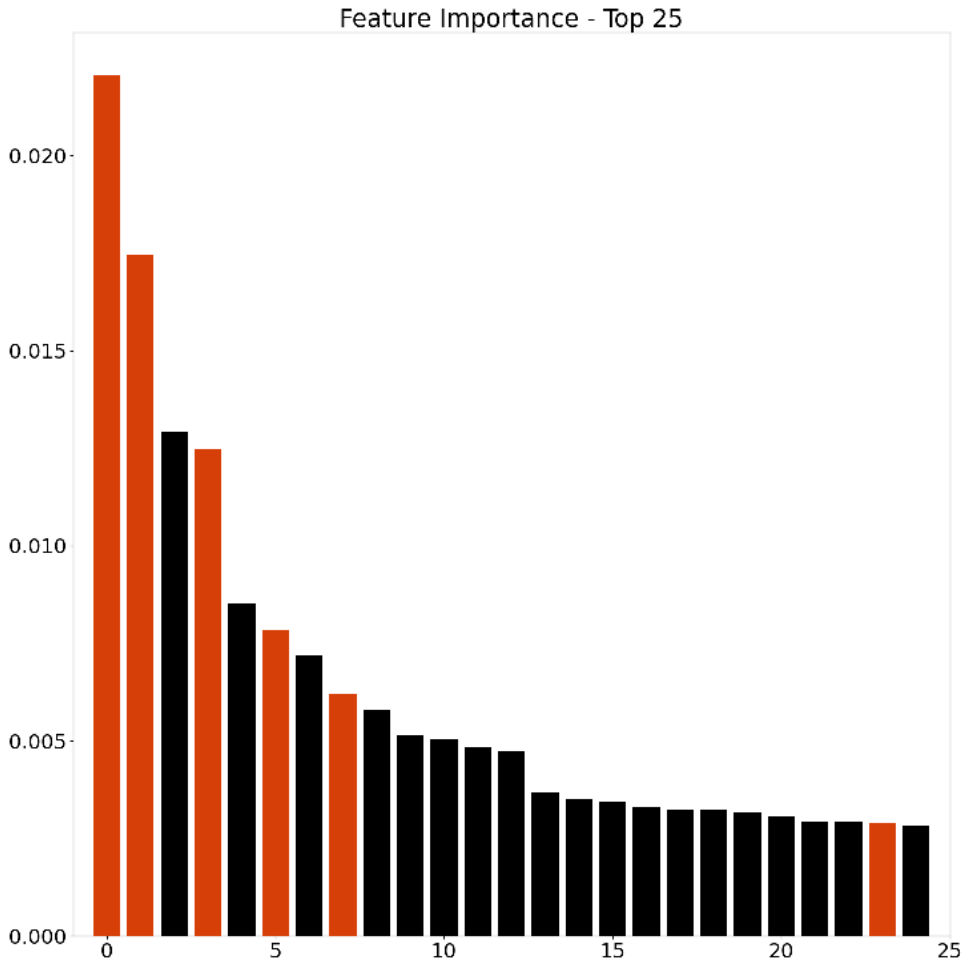

Figure 13: A representation of the top 25 selected features. Highlighted – valence/arousal features

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Results – Feature Selection

- VAD – Sentiment Intersect
- MPQA, EmoLex

Index	Feature Name	Correlation
5	EmoVad_^_EmoLex_glob_v_positive_mean	0.0085
9	EmoVad_^_MPQA_a_positive_max_words_std	0.0058
10	BsmVad_^_EmoLex_d_positive_most_words_mean	0.0051
14	EmoVad_^_EmoLex_glob_v_negative_mean	0.0036
16	EmoVad_^_EmoLex_glob_a_positive_std	0.0034

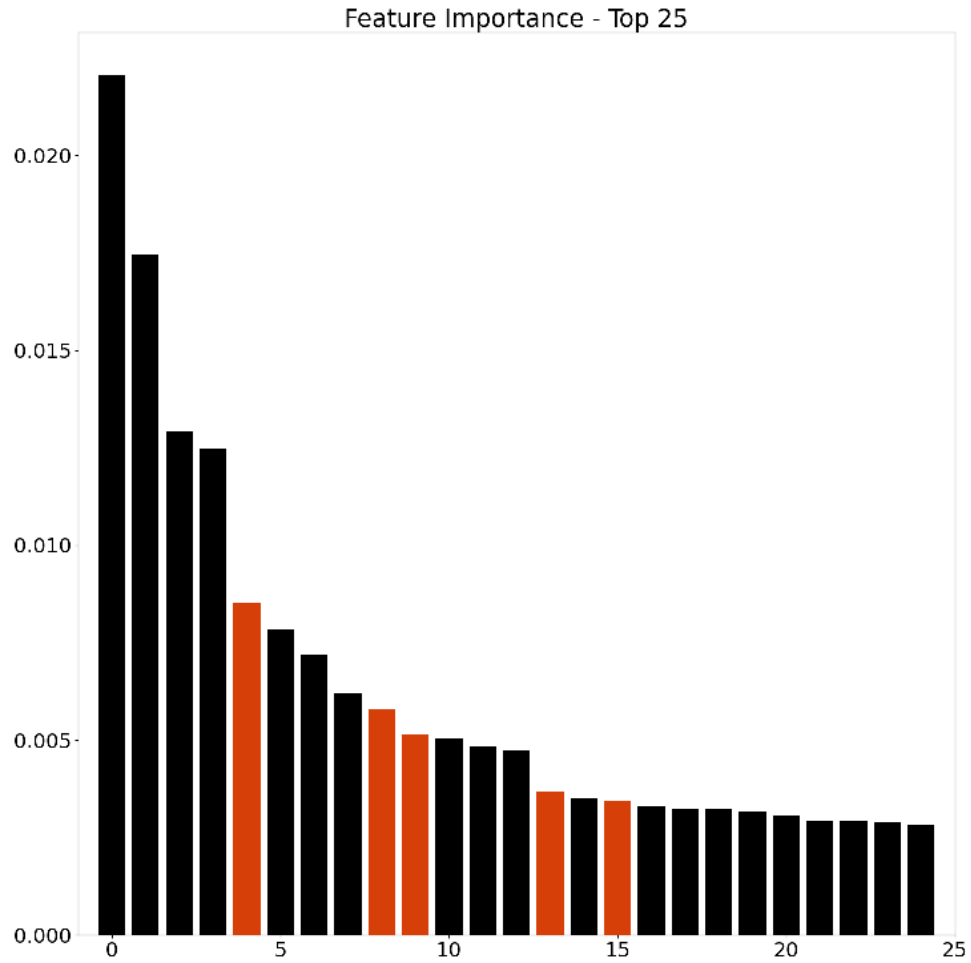

Figure 14: A representation of the top 25 selected features. Highlighted – sentiment U valence/arousal features

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Results – Feature Selection

- EmoAff – Anger Affect
- Total Variance – 14.48%
- 880 total features

Index	Feature Name	Correlation
3	EmoAff_anger_means_mean	0.0129
7	EmoAff_anger_means_std	0.0071
13	EmoAff_anger_uniq_means_mean	0.0047
21	EmoAff_anger_uniq_means_std	0.0030

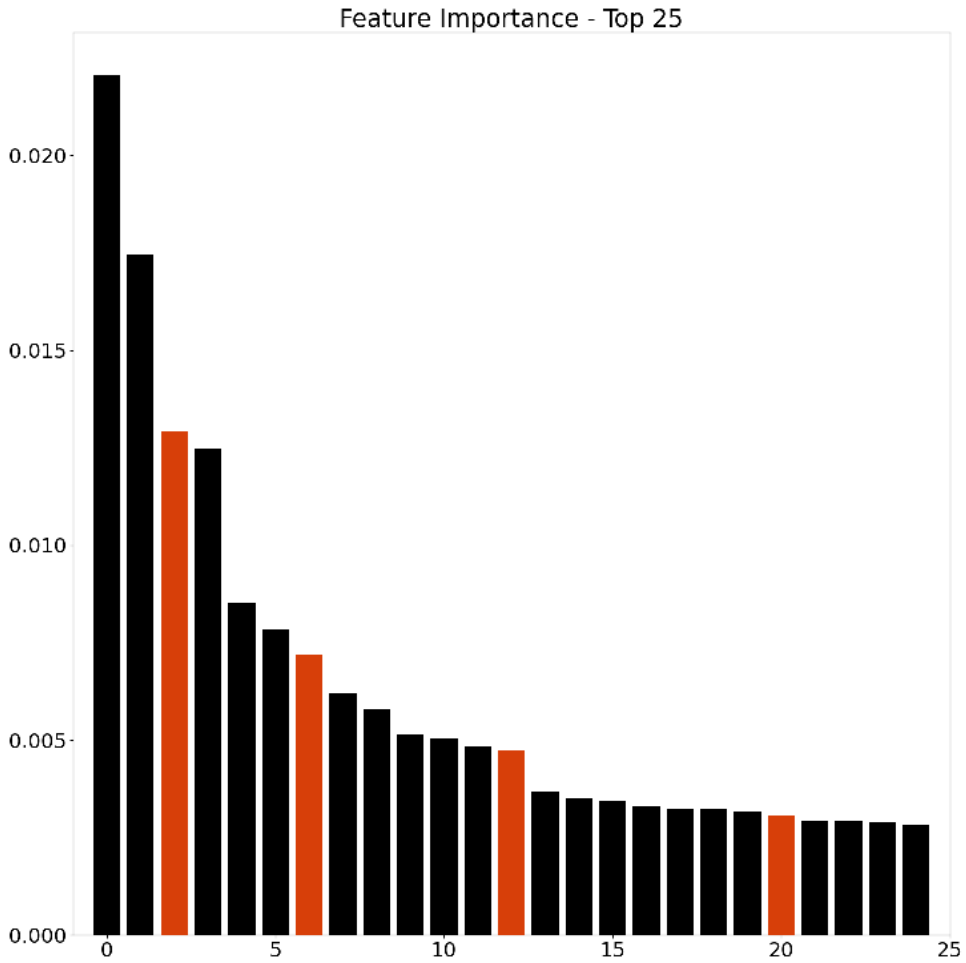

Figure 15: A representation of the top 25 selected features. Highlighted – anger affect features

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Conclusion & Future Work

- Contributed a feature generation framework
- Future work – Train model to predict valence, arousal
- Mood classification for songs

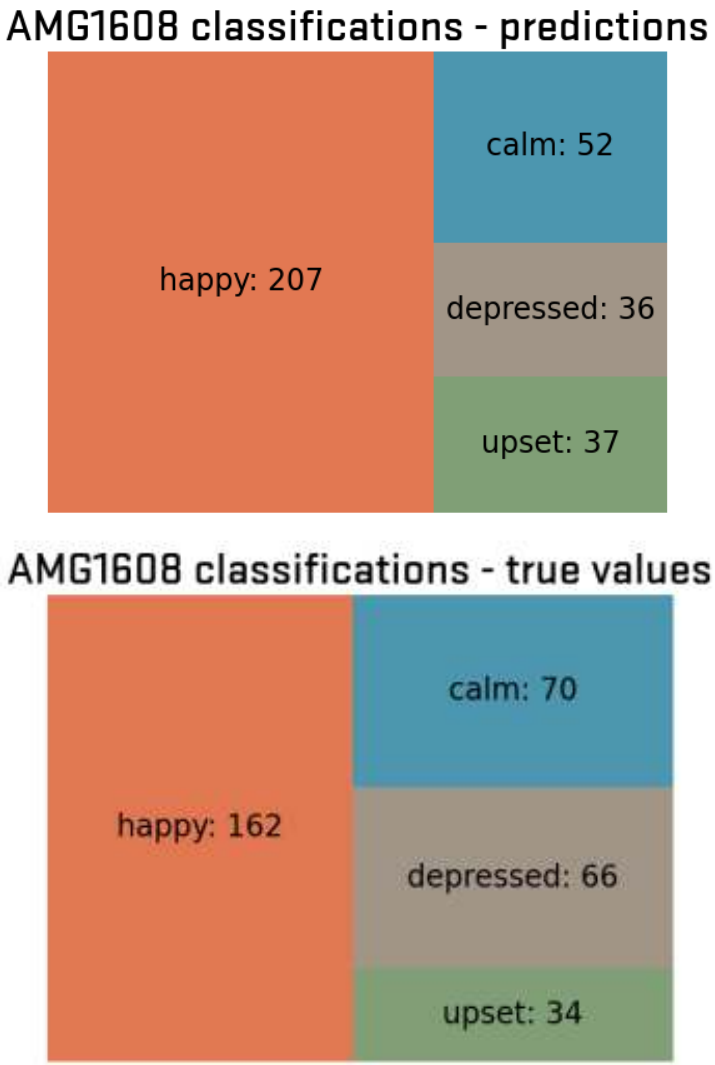

Figure 16, 17: Categorization of songs from AMG1608 based on positive or negative valence and arousal. Predictions compared to actual measurements.

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Works Cited

[1] A. B. Warriner, V. Kuperman, and M. Brysbaert, “Norms of valence, arousal, and dominance for 13,915 English lemmas,” Behav Res, vol. 45, no. 4, pp. 1191–1207, Dec. 2013, doi: 10.3758/s13428-012-0314-x.

Note – Extended ANEW dataset references here

[2] S. Mohammad, “Obtaining Reliable Human Ratings of Valence, Arousal, and Dominance for 20,000 English Words,” in Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), Melbourne, Australia, 2018, pp. 174–184, doi: 10.18653/v1/P18-1017.

Note – The EmoVAD dataset references here

[3] S. Mohammad, "Word Affect Intensities", *Proceedings of the 11th Edition of the Language Resources and Evaluation Conference (LREC-2018)*, 2018. [Accessed 1 April 2021].

Note – The EmoAff dataset references here

[4] S. M. Mohammad and P. D. Turney, “Crowdsourcing a Word-Emotion Association Lexicon,” arXiv:1308.6297 [cs], Aug. 2013, Accessed: Nov. 04, 2020. [Online]. Available: http://arxiv.org/abs/1308.6297.

Note – the EmoLex dataset references here

Works Cited [cont]

[5] Y.-A. Chen, Y.-H. Yang, J.-C. Wang, and H. Chen, “The AMG1608 dataset for music emotion recognition,” in *2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, South Brisbane, Queensland, Australia, Apr. 2015, pp. 693–697, doi: 10.1109/ICASSP.2015.7178058.

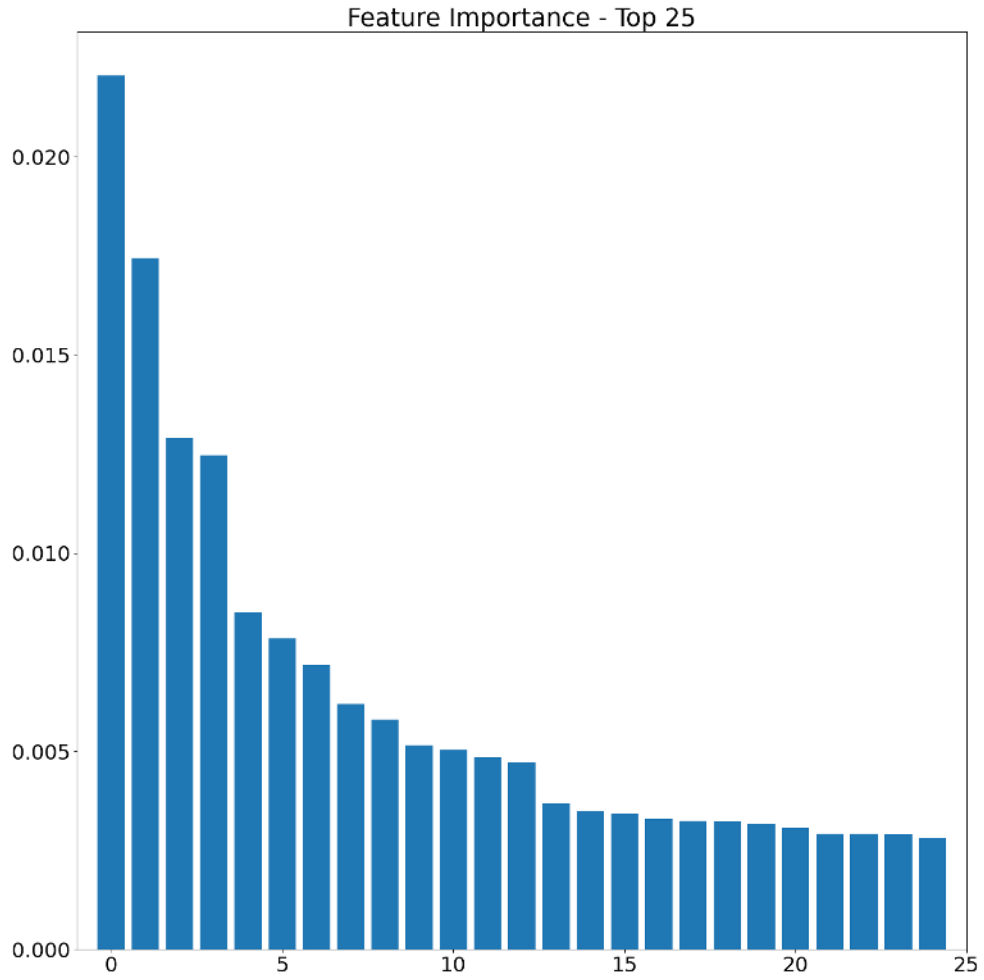
[6] Y. Choi and J. Wiebe, “+/-EffectWordNet: Sense-level Lexicon Acquisition for Opinion Inference,” in *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, Doha, Qatar, 2014, pp. 1181–1191, doi: 10.3115/v1/D14-1125.’

Note – The MPQA dataset references here

[7] M. M. Bradley and P. J. Lang, “Affective Norms for English Words (ANEW): Instruction Manual and Affective Ratings,” p. 49.

[8] R. Delbouys, R. Hennequin, F. Piccoli, J. Royo-Letelier, and M. Moussallam, “MUSIC MOOD DETECTION BASED ON AUDIO AND LYRICS WITH DEEP NEURAL NET,” p. 6, 2018.

Appendix A – Feature Selection



Feature Name	Correlation Score
EmoVAD_glob_a_mean	0.0220
EmoVAD_glob_a_uniq_mean	0.0174
EmoAff_anger_means_mean	0.0129
EmoVAD_glob_a_uniq_std	0.0124
EmoVad_^_EmoLex_glob_v_positive_mean	0.0085
EmoVAD_glob_v_mean	0.0078
EmoAff_anger_means_std	0.0071
BsmVAD_glob_a_uniq_mean	0.0061
EmoVad_^_MPQA_a_positive_max_words_std	0.0058
BsmVad_^_EmoLex_d_positive_most_words_mean	0.0051
EmoVAD_glob_a_std	0.0050
BsmVAD_glob_d_uniq_mean	0.0048
EmoAff_anger_uniq_means_mean	0.0047
EmoVad_^_EmoLex_glob_v_negative_mean	0.0036
EmoLex_glob_sadness_uniq_mean	0.0034
EmoVad_^_EmoLex_glob_a_positive_std	0.0034
EmoVAD_glob_a_ratio	0.0032
EmoVAD_a_stds_std	0.0032
EmoVad_^_MPQA_glob_d_negative_mean	0.0032
EmoVAD_glob_v_uniq_mean	0.0031
EmoAff_anger_uniq_means_std	0.0030
EmoVad_^_MPQA_glob_v_negative_mean	0.0029
EmoVad_^_EmoLex_glob_a_positive_uniq_std	0.0029
EmoVAD_v_uniq_stds_mean	0.0028
BsmVad_^_EmoLex_glob_d_positive_mean	0.0028

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