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Music Mood Classification: From a Music Piece to a Computed Mood

Seminar SS15: Topics in Computer Music

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Overview

- Motivation
- State of the Art
 - Music Mood Classification
 - Emotion Models
 - Music Features
 - Ground Truth
 - Supervised Machine Learning
 - Different Types of Labeling
- Exemplary Approach
 - Idea
 - Methods
 - Results & Review
- Conclusion



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Motivation

- State of the Art
- Exemplary Approach
- Conclusion

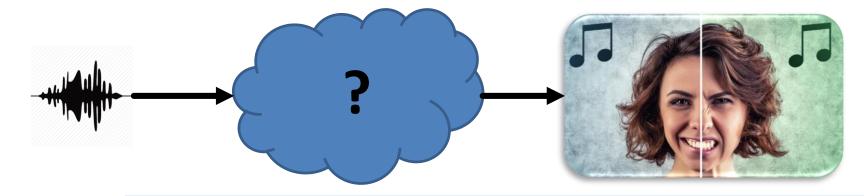
Motivation – Game Development

Suitable music to a specific situation ...





... but too much to handle manually!



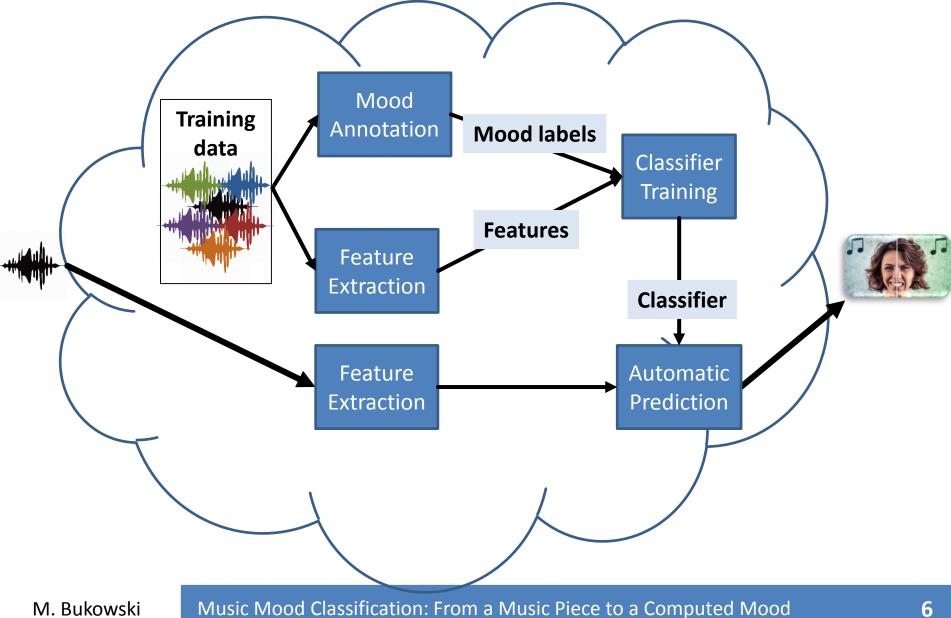
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✓ Motivation

State of the Art

- Exemplary Approach
- Conclusion

State of the Art – Music Mood Classification

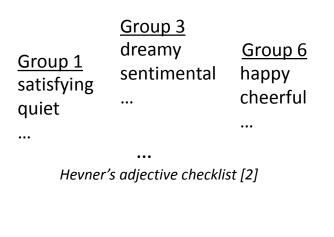


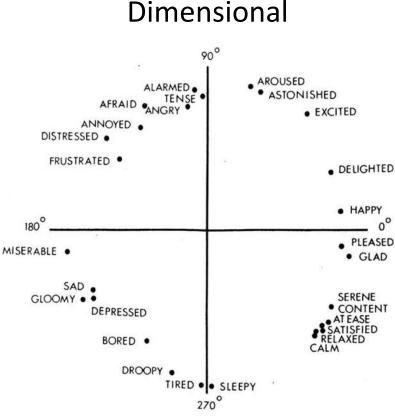
${\tt State of the Art-Emotion Models}$

Active topic in psychology research [1]

VS.

Categorical



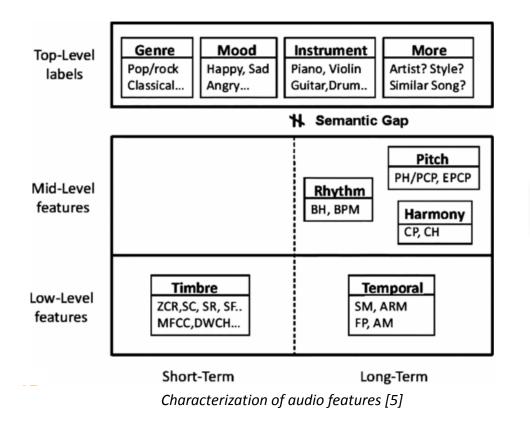


- Problems
 - No standards
 - Oversimplification / Ambiguity
 - Distinction

Circumplex Model [3]

State of the Art – Music Features

 "Any classification system is only as good as the features that it receives." [4]





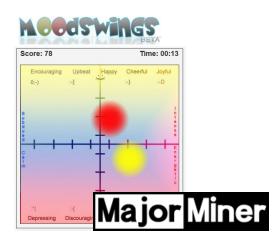
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State of the Art – Ground Truth

- Problems
 - Emotional perception (subjectivity)
 - Emotion annotation (labor-intensive, time consuming)
 - Different mood models and (small) datasets

- How is it done?
 - Experts
 - Social Tagging
 - Annotation Games

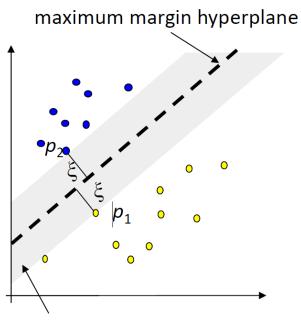




State of the Art – Supervised Machine Learning

- General Problem:
 - Classifier needed to predict labels for unseen data
 - Mapping from feature space to output mood labels
 - Training with ground truth data

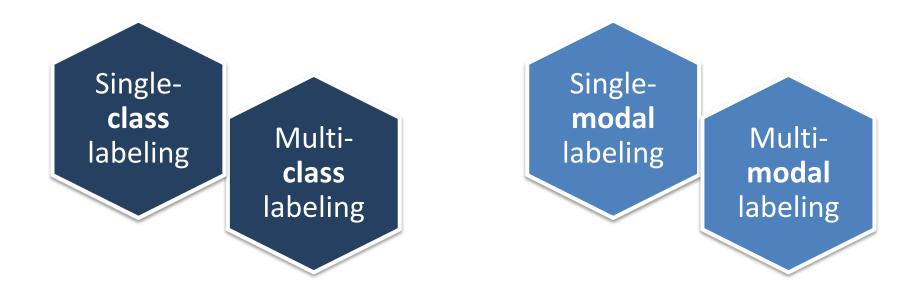
- Most popular classifier:
 - Support Vector Machine (SVM)





Support Vector Machines: Principle [6]

State of the Art – Different Types of Labeling





Variety of approaches!

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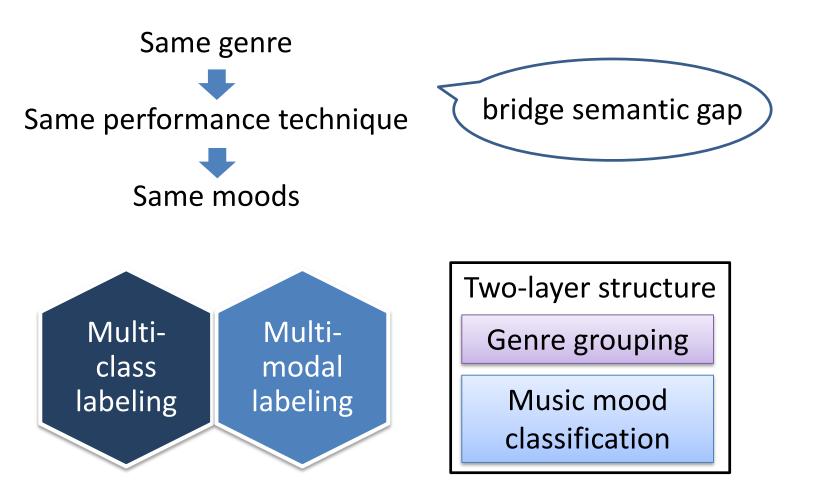
✓ Motivation

✓ State of the Art

Exemplary Approach

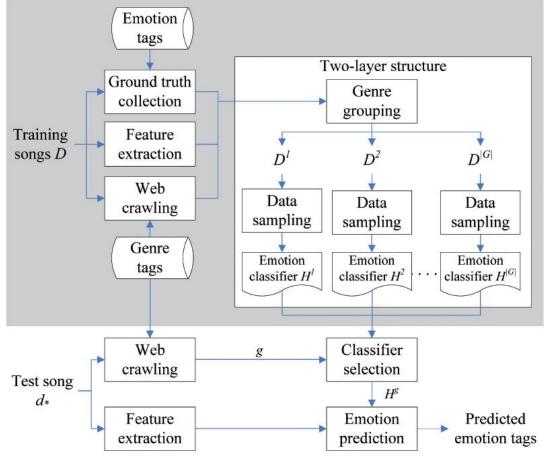
Conclusion

"Exploiting Online Music Tags for Music Emotion Classification" [7]



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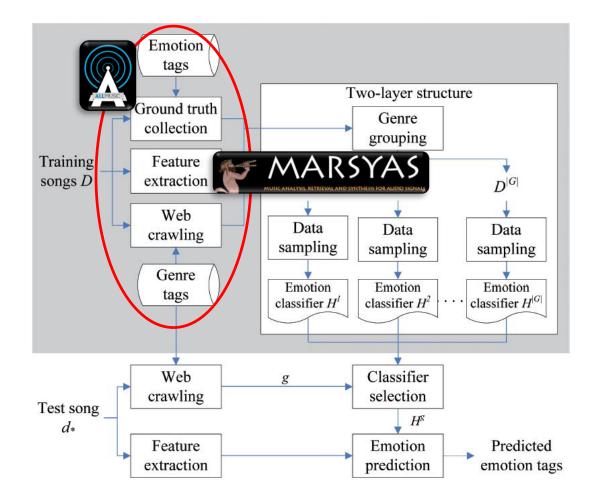
Exemplary Approach – Methods: System Overview



System diagram [7]

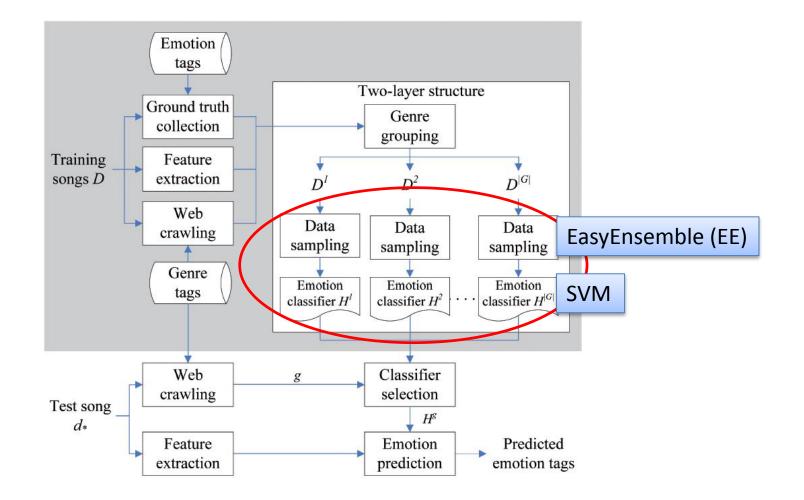
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Exemplary Approach – Methods: Ground Truth & Features



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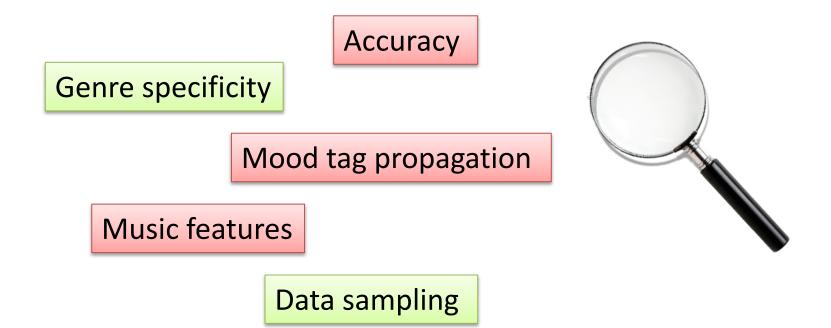
Exemplary Approach – Methods: Sampling and Classification



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Exemplary Approach – Results & Review

- Genre-specific characteristics of songs (similarity)
- Improvement of the average F-score from 0.23 to 0.36



One exemplary 'successful' approach with lack of comparability

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- ✓ Motivation
- ✓ State of the Art
- ✓ Exemplary Approach

Conclusion

Conclusion

- Need for computing moods from music pieces
- Variety of solutions
- Best systems use a combination of features and information from multiple domains
- Open issues regarding its multidisciplinary nature
- Research field is quite young





Great potential and basis for further research!

References (1)

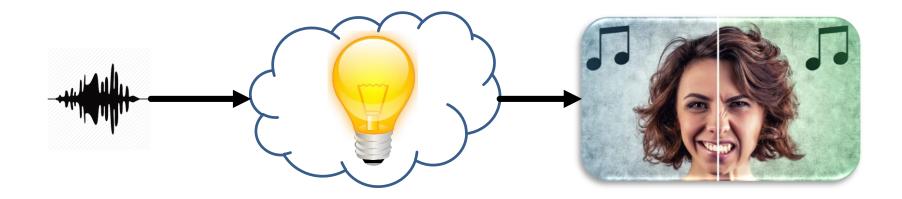
- [1] Music Emotion Recognition: A State of the Art Review, Kim, Y. E., Schmidt, E. M., Migneco, R., Morton, O. G., Richardson, P., Scott, J., Speck, J. A. & Turnbull, D., 11th International Society for Music Information and Retrieval Conference, pp. 255-266, 2010
- [2] Experimental Studies of the Elements of Expression in Music, Hevner, K., The American Journal of Psychology, Vol. 48, pp. 246-268, 1936
- [3] A Circumplex Model of Affect, Russel, J. A., Journal of Personality and Social Psychology, Vol. 93, pp. 1161-1178, 1980
- [4] Machine Recognition of Music Emotion: A Review, Yang, Y.-H. & Chen, H. H.
 ACM Transactions on Intelligent Systems and Technology (TIST), Vol. 3, pp. 40:1-40:30, 2012

References (2)

- [5] A Survey of Audio-Based Music Classification and Annotation, Fu, Z., Lu, G., Ting, K. M. & Zhang, D., IEEE Transactions on Multimedia, Vol. 13, pp. 303-319, 2011
- [6] Data Mining Algorithms: Chapter 5, Sander, J. & Ester, M., Lecture Notes, RWTH Aachen University, Data Management And Exploration Group, Prof. Dr. rer. nat. Thomas Seidl, 2013
- [7] Exploiting Online Music Tags for Music Emotion Classification, Lin, Y.-C.; Yang,
 Y.-H. & Chen, H. H., ACM Trans. Multimedia Comput. Commun. Appl., Vol. 7S,
 pp. 26:1-26:16, 2011
- [8] Exploring Mood Metadata: Relationships with Genre, Artist and Usage Metadata, Hu, X. & Downie, J. S., Proceedings of the 8th International Conference on Music Information Retrieval, 2007, 67-72



Thank you for your attention!



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Appendix – Outlook

Personalized systems with individual profiling

Consider







Applications

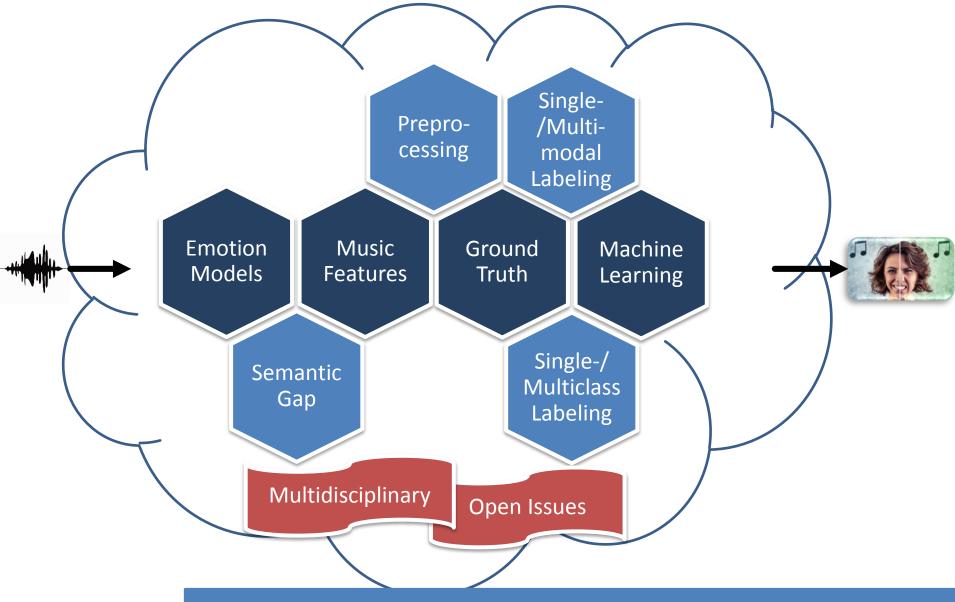






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Appendix – Music Mood Classification (Several Parts)



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Appendix – Hevner's Emotion Model

8 vigorous	7 exhilarated soaring triumphant dramatic passionate sensational agitated exciting impetuous restless	6 merry joyous gay happy cheerful bright	5 humorous playful whimsical fanciful quaint sprightly delicate light graceful	4 Ivrical
robust emphatic martial ponderous majestic exalting				leisurely satisfying serene tranquil quiet soothing
	1 spiritual lofty awe-inspiring dignified sacred solemn sober serious	2 pathetic doleful sad mournful tragic melancholy frustrated depressing gloomy heavy dark	3 dreamy yielding tender sentimental longing yearning pleading plaintive	

Hevner's adjective checklist [2]

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Cluster1	Cluster2	Cluster3	Cluster4	Cluster5
Rowdy	Amiable/	Literate	Witty	Volatile
Rousing	Good natured	Wistful	Humorous	Fiery
Confident	Sweet	Bittersweet	Whimsical	Visceral
Boisterous	Fun	Autumnal	Wry	Aggressive
Passionate	Rollicking	Brooding	Campy	Tense/anxious
	Cheerful	Poignant	Quirky	Intense
			Silly	

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Appendix – Ground Truth: AllMusic.com



183 mood classes

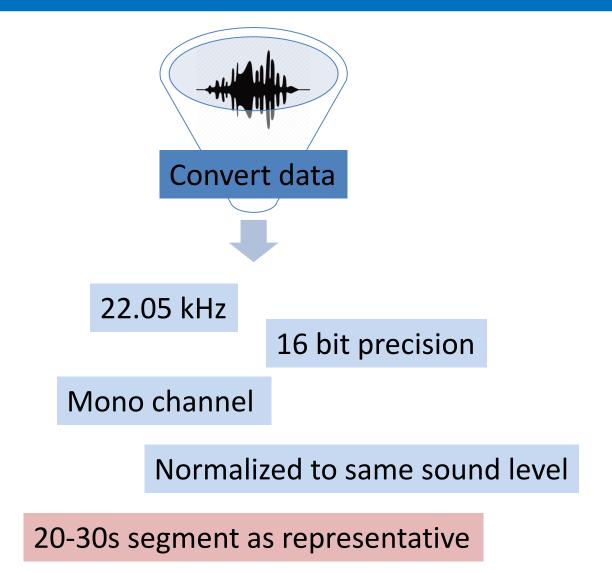
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New Releases	Discover	Articles	Video	Recommendations	My Profile	Advanced Search	Sign Up L

Moods

Acerbic	Elegant	Mechanical	Sensual
Aggressive	Elegiac	Meditative	Sentimental
Agreeable	Energetic	Melancholy	Serious
Airy	Enigmatic	Menacing	Severe
Ambitious	Epic	Messy	Sexual
Amiable/Good-Natured	Erotic	Mighty	Sexy
Angry	Ethereal	Monastic	Shimmering
Angst-Ridden	Euphoric	Monumental	Silly
Anguished/Distraught	Exciting	Motoric	Sleazy
Angular	Exotic	Mysterious	Slick
Animated	Explosive	Mystical	Smooth
Apocalyptic	Extroverted	Naive	Snide
Arid	Exuberant	Narcotic	Soft/Quiet
Athletic	Fantastic/Fantasy-like	Narrative	Somber
Atmospheric	Feral	Negative	Soothing
Austere	Feverish	Nervous/Jittery	Sophisticated
Δutumnal	Fierce	Nibiliefic	Spacev

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Appendix – Before Extraction: Preprocessing



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Appendix – Exemplary Approach: Results

- Genre-specific characteristic of songs (similarity)
- Improvement of the average F-score

Classifier	# layer	Precision	Recall	F-score	# tags per album]
Random guess		0.07	0.59	0.12	106.79]
SVM		0.09	0.02	0.03	0.28	
SVM+EE	One	0.12	0.63	0.20	69.24	
SVM+EE+TS		0.30	0.19	0.23	7.57	
SVM		0.51	0.18	0.27	3.30	
SVM+EE	Two	0.14	0.59	0.23	54.75	Experim Classifyi
SVM+EE+TS		0.38	0.35	0.36	11.21	Classes

nental Result for ing 183 Emotion [7]

0	System	Precision	Recall	F-score	
mirex	Random guess	0.39	0.54	0.45	Classification Result for the
	One-layer	0.58	0.61	0.59	Five-Class MIREX Emotion
e	Two-layer	0.61	0.65	0.63	Taxonomy [7]