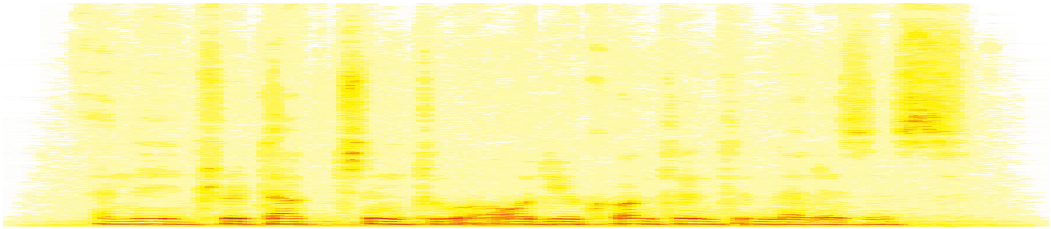
Introduction to Audio Content Analysis

Module 8.3: Mood Recognition

alexander lerch



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introduction

overview

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corresponding textbook section

Chapter 8: Musical Genre, Similarity, and Mood (pp. 158–161)

- **lecture content**
  - introduction to emotion and mood
  - models for mood
  - linear regression

- **learning objectives**
  - describe Russel's arousal-valence plane
  - discuss commonalities and differences between mood recognition and genre classification
  - implement linear regression in Matlab

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mood recognition

introduction

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- **objective**:identify mood/emotion of a song
- **terminology**:
  - *Music Mood Recognition* and *Music Emotion Recognition* usually used synonymously
- **processing steps** (similar to genre and similarity tasks)
  - extract features
  - classify (possibly regression)

mood recognition

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mood recognition

challenges

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What is the difference between mood and emotion

mood recognition

challenges

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What is the difference between mood and emotion

- *emotion*:
  - temporary, evanescent
  - (directly) related to external stimuli
- *mood*:
  - longer term, stable
  - diffuse affect state

mood recognition

challenges

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- **ground truth data**
  - *verbalization* of emotions/moods usually misleading
  - not easily *quantifiable*/categorizable
  - change over time?
- **research focus**
  - are established *basic emotions* (happiness, anger, fear, ...) representative for music perception
  - *aroused vs. transported* moods?

mood recognition

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mood recognition

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mood recognition

models

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- classification into **label clusters**[1]

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Rowdy	Amiable/Good Natured	Literate	Witty	Volatile
Rousing	Sweet	Wistful	Humorous	Fiery
Confident	Fun	Bittersweet	Whimsical	Visceral
Boisterous	Rollicking	Autumnal	Wry	Aggressive
Passionate	Cheerful	Brooding	Campy	Tense/Anxious
		Poignant	Quirky	Intense
			Silly	

- **mood model**, circumplex model[2]

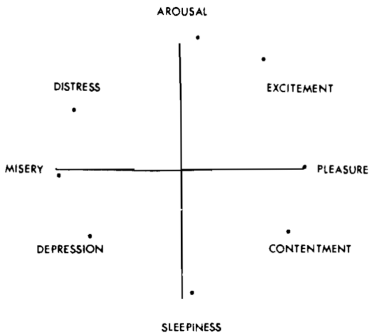
[1] X. Hu and J. S. Downie, "Exploring Mood Metadata: Relationships with Genre, Artist and Usage Metadata," in *Proceedings of the International Society for Music Information Retrieval Conference (ISMIR)*, Vienna, 2007.

[2] J. A. Russel, "A Circumplex Model of Affect," *Journal of personality and social psychology*, vol. 39, no. 6, pp. 1161–1178, 1980, ISSN: 1939-1315(Electronic);0022-3514(Print). DOI: 10.1037/h0077714.

mood recognition

models

- classification into **label clusters**[1]
- **mood model**, circumplex model[2]



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mood recognition

mood model: regression modeling

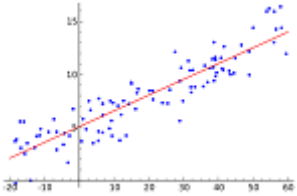
- **mapping**
  - (N-dimensional) observation (feature) to 2-dimensional coordinate (valence/arousal)
- **training**
  - find model to minimize error between data points and "prediction"

linear regression

introduction to regression 1/2

- fit a linear function to a series of points (x_j, y_j)

$$y_n = m \cdot x_n + b$$



https://en.wikipedia.org/wiki/Linear_regression

linear regression

introduction to regression 2/2

- minimize error between model and data (here: least squares)

$$
\begin{aligned}
e_n^2 &= (y_n - mx_n - b)^2 \\
E &= \sum (y_n - mx_n - b)^2
\end{aligned}
$$

linear regression

introduction to regression 2/2

- minimize error between model and data (here: least squares)

$$\begin{aligned} e_n^2 &= (y_n - mx_n - b)^2 \\ E &= \sum (y_n - mx_n - b)^2 \end{aligned}$$

$$\frac{\partial E}{\partial b} = \sum -2(y_n - mx_n - b) = 0$$

$$\frac{\partial E}{\partial m} = \sum -2x_n(y_n - mx_n - b) = 0$$

linear regression

introduction to regression 2/2

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$$\frac{\partial E}{\partial m} = \sum -2x_n(y_n - mx_n - b) = 0$$

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\end{aligned}
$$

$$
\begin{aligned}
&\Rightarrow \\
m &= \frac{\mathcal{N}\sum x_n y_n - \sum x_n \sum y_n}{\mathcal{N}\sum x_n^2 - (\sum x_n)^2} \\
b &= \frac{\sum y_n}{\mathcal{N}} - m\frac{\sum x_n}{\mathcal{N}}
\end{aligned}
$$

mood recognition

range of results

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- highly dependent on data
- **5 mood clusters**:
  40–60% classification rate
- **mood model**:
  0.1–0.4 absolute prediction error (unit circle)

mood recognition

range of results

- highly dependent on data
- **5 mood clusters**:
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summary

lecture content

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- **emotion and mood**
  - emotion: temporary, related to external stimuli
  - mood: long term, diffuse affective state
- **features**
  1. baseline features are identical to genre and similarity tasks
- **inference**
  1. often done as regression (as opposed to classification)