sketches

mardi 29 avril 2025 1:37 a.m.

Tzatenakis / Cook (2002):
- ↳ Compiled DS of 2,300 tracks across 23 genres.
- ↳ Used both timbral / non-timbral features, but timbral were most important (MFCCs, spectral centroid, spectral rolloff, spectral flux, ~~spectral~~ zero crossing rate) first 5 means and variance.
- ↳ Tried a few different classification methods.
  - → k-nearest neighbors. — still good comparable to gaussian classifier.
  - → Gaussian Mixture Models ~~...~~ → most effective in their testing
  - → Gaussian Classifier →
- Conclusion: Use timbral features, to get accurate classification.

Bhalke et. al (2017):
- ↳ 4 genres across 2 datasets (Rock/Classical; Tamil Folk/Classical, both n≈100-150 songs)
- ↳ Used mainly timbral features like T and C (2002)
- ↳ ~~Used KNN~~ Trained a KNN and a SVM classifier. (RBF kernel) using two feature sets.

Tamil genre
- ~~KNN~~ → Set 1: Spectral Roll off, Flux, Skewness, kurtosis, MFCC.
- ~~SVM~~ → Set 2: " " " " Fract. MFCC
- ~~Tamil Genres (Both knn and SVM)~~ (B → Both knn / SVM
- 1: KNN 66 %, SVM 83.5%
- 2: knn 70%, SVM 96%

Western genres →
- Set 1: Spectral Roll off, Flux, MFCC.
- Set 2: " " Fract. MFCC.
- → Only SVM → 1: 80%, 2: 96.25%

goal of 50%

Chen et al. (2009):
- ↳ SVM with 1 dataset of MFCCS and log energy (both on short + long term ~~clips~~ sampling frames.)
- ↳ Used with exponential radial basis kernel. and ~~...~~ variable frame length when calculating MFCCs.

Conclusion Using an SVM with timbral features should build a good classifier.

Use classifier confidence to reflect how genre-like a particular AI music is.
↳ show if classifiers be fooled.

Weakness:
→ FMA uses 30 sec clips →

The Question: How human-like is AI-generated music?
↳ Answer by building classifier on human music, then trying to have it classify AI-generated music.

~~- First 15 MFCCs~~
~~- First 25 MFCCs~~

Cleaning
- MFCCS
- spectral centroid
- spectral rolloff
- spectral flux
- zero crossing rate

Goal Data set.

Song id	genre	mfcc-1	...	mfcc-15	centroid_mean	centroid_var
0						
1						
2						
⋮						

Tzatenakis/Cook (2002)

Idea: Use FMA data with Tzatenakis/Cook method to build a classifier.

They used:
- Simple Gaussian Classifier
- Gaussian Mixture Model
- K nearest

Similar perf.

↳ Which data most important:
- ↳ MFCCS
- ↳

Data Visualizations / Tables
2-3

Types of genres in the dataset

- Final Variable list
- ~~track-id~~
- ~~genre-top~~

Weakness: Too many genres.
Solution: 10-15 genres.

N

~~track id, artist name~~

track_id, title, artist_name, genre_top, mfcc-1, ⋮, mfcc_15
centroid_mean, centroid_variance, rolloff_mean, roll off_variance, flux_mean, flux_variance, zcr_mean
zcr_variance.

FrFT: Fractional Fourier Transform

Topics//

- Using AI to measure AI
- Model selection
-

Topics: What are some discussions.

- Is using AI to measure AI alright?
- If the classifier is shit what does this mean for AI systems as a whole?
- Impacts of AI-generated music on Music Information Retrieval Systems
- What weaknesses does their work have?
- Where can this work go?
-

could maybe asking a human to classify be a better idea?

Bias in classifiers, only some music gets selected

Things like Suno.

could AI systems tailor themselves to the whims of classifiers to be pure.

~~Proble~~

Weaknesses:

- Used a small music gen model
- Very Biased data set
- Prompts are inherently stochastic in nature → random seeds for reproducibility because of model.

Next Steps

- Repeat experiment with more powerful music generation tool
- Get new data set that is more balanced, or try finding more examples
- Train the models with more extensive testing and cross validation
- maximum performance

- Get new data set that is more balanced, or try[illegible]
- Train the models with more extensive testing and cross validation phases to ensure maximum performance
- Investigate low tech experimental methods, such as comparing human listeners with ~~[illegible]~~ trained machine classifiers.

What did we learn.

- On the use of classifiers as a measure of humanness

Left to do:

- ~~Write prompts~~
- ~~Create 20, 30s clips~~
    - ~~10 w Music GPT~~
    - ~~10 w Suno (or smth)~~
- ~~Extract the features~~ use Classifier.
- Compare results. → Simple to implement.
- Write paper
    - ~~Write results~~ Classifier / ~~Performance~~
    - ~~Music GPT part Results~~ Music GPT part
    - Results
        - Training
        - Classification Task.
    - Discussion
        - Implications for ~~AI~~ Music ~~Industry~~ ians
        - Weaknesses

30
~~15~~·3 ~ 25m
15·3 ~ 12 m
15·5 ~ 20 m