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Classification

Machine Learning and Pattern Classification

Labeling Functions Accuracy

Goal: Evaluate how well our rule-based labeling functions identify acoustic events from audio data, balancing precision and recall.

Overall Performances:

- <u>Macro-F1</u>: 0.451
- <u>Micro-F1</u>: 0.443
- <u>Precision</u>: 0.466
- <u>Recall</u>: 0.421

Classes with good performances:

- Violin (F1 ≈ 0.72)
- Saxophone (F1 ≈ 0.72)
- Piano (F1 ≈ 0.66)
- Vacuum Cleaner (F1 ≈ 0.57)

Problematic classes

- Broadband noise (waves, fire) ~ 800 False Positives
- Short events (bicycle squeak, sneeze) low recall due to strict thresholds (duration/energy)

Most Discriminative Audio Features

Goal: Identify audio features (MFCCs, zero-crossing rate) that best distinguish event classes.

Mutual Information Analysis:

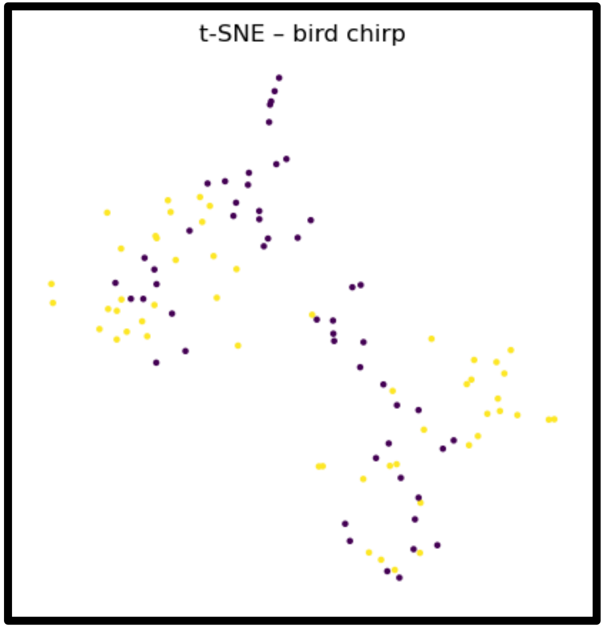
- Strongly discriminative features identified:
  Airplane: MFCC-1 and zero-crossing rate
  Rain: MFCC-0 and MFCC-5
- Problematic classes show a flat MI profile, meaning no single distinctive feature
- Low-order MFCCs and zero-crossing rate strongly distinguish harmonic/stationary sounds.
- Current features insufficient for impulsive or spectrally overlapping events

Clustering of Audio Features

Goal: Assess whether audio features naturally group into tight clusters corresponding to event classes

Quantitative Clustering Evaluation:
Silhouette Score: very low (max 0.008 for cow moo, sewing machine)
Davies-Boulding Index: very high (10-14, e.g., saxophone = 14)

Considerations:
Very weak clusters, strong overlap among classes
Features lack separability, implying difficulties for simple linear classifier



t-SNE embedding of MFCC and zero-crossing rate features for class "bird chirp". Yellow points are positive examples; purple points are negative examples.