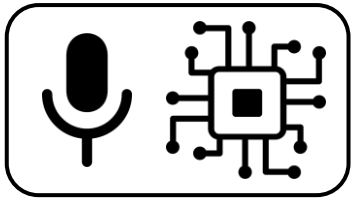
Computational Analysis of Sound and Music

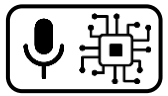


Environmental Sound Analysis – Acoustic Scene Classification

Dr.-Ing. Jakob Abeßer

Fraunhofer IDMT

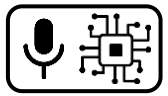
jakob.abesser@idmt.fraunhofer.de



Acoustic Scene Classification

Outline

- Introduction & Application Scenarios
- Traditional Approaches
- Deep Learning-based Approaches
- Current research topics
    - Domain adaptation
    - Efficient models



Acoustic Scene Classification

Introduction

- Acoustic scene classification (ASC)
  - Multi-class (1 of N) classification scenario
  - Summative label (tagging)
- Common Classes
  - Indoor
    - Airport, shopping mall, metro station
  - Outdoor
    - Pedestrian street, urban park, traffic
  - Transportation
    - Travelling by bus / metro / tram

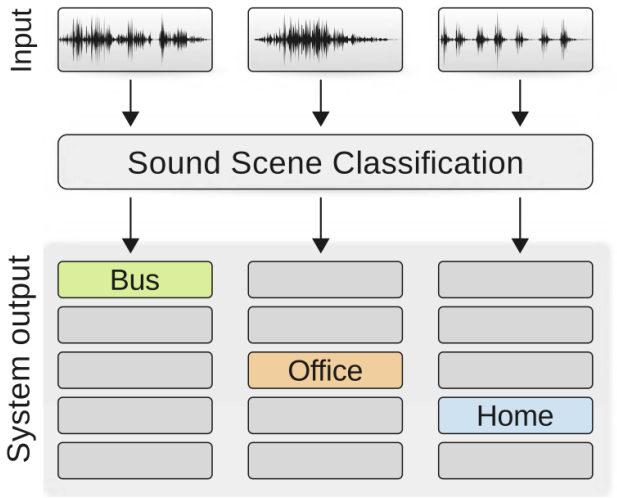


Fig-E3-1

Acoustic Scene Classification

Introduction

- Interdependence between sound events and acoustic scenes
- Acoustic scene
    - Typical set of sounds
    - Example: Office
        - Keyboard clicks
        - Human conversations
        - Printer
        - Air conditioner

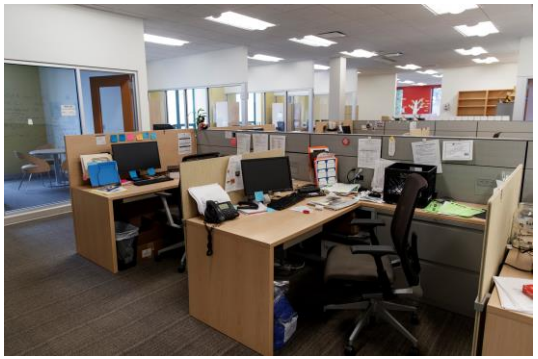


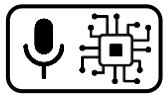
Fig-E3-2

Aud-E3-1

Acoustic Scene Classification

Application Scenarios

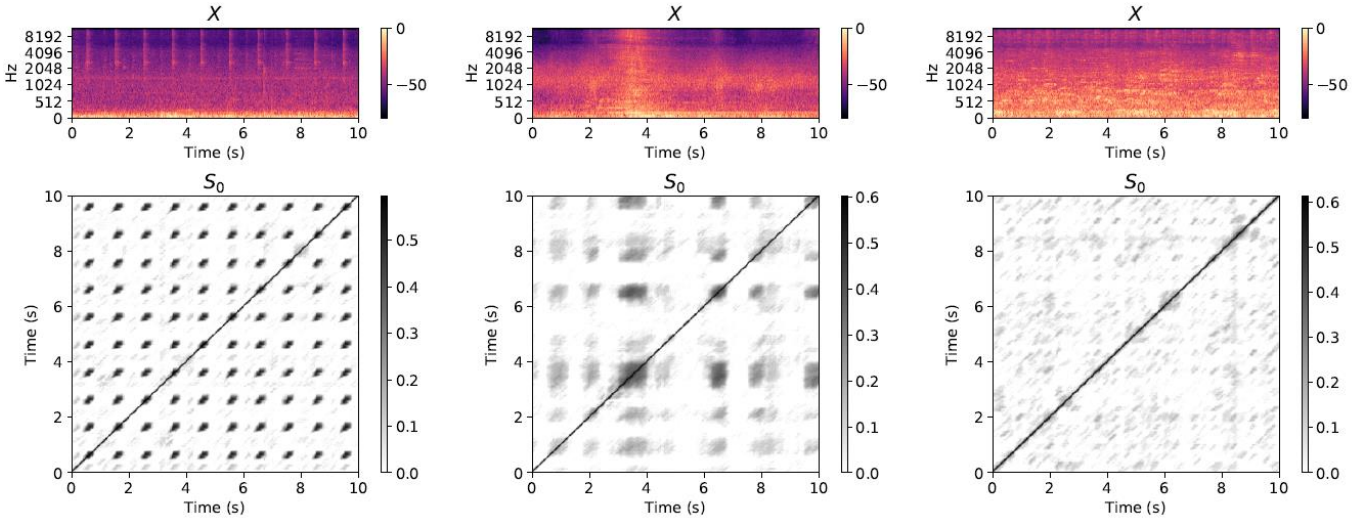
- Context-aware devices (hearables, cell phones)
- Smart cities (improve city planning, traffic management, and public safety)
- Content analysis (indexing and organizing multimedia content)
- Human-computer interaction (natural interaction with devices through voice commands and ambient sound recognition)
- Healthcare (monitoring patients' acoustic environments in hospitals or homes)



Acoustic Scene Classification

Traditional Approaches

- Timbre-related features (MFCC, Mel Spectrogram)
- Classification algorithms (SVM, GMM)
- Recurrence Quantification Analysis (RQA) [Roma et al., 2014]
  - Measure sound repetitively in acoustic scenes



Regular repetitions (beeps from tram doors)

Irregular repetitions (passing cars)

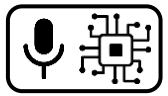
No repetitions (shopping mall)

Fig-E3-3

Acoustic Scene Classification

Deep Learning-based Approaches

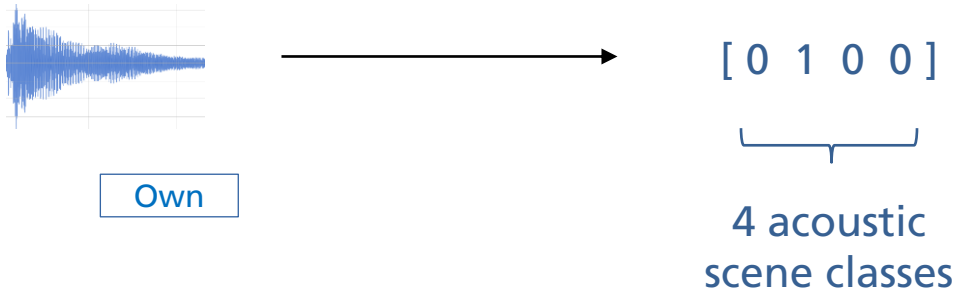
- General design choices
  - CNN & CRNN models (similar to SED)
  - Temporal result aggregation (pooling) within network
  - Final layer: Softmax activation function (multiclass classification)
  - Data Augmentation
    - Mixup
    - SpecAugment
  - Ensemble models



Acoustic Scene Classification

Deep Learning-based Approaches

- Label encoding
  - One-hot-encoded (global) target
- Example
  - 4 scene classes (bus, office, home, forest)
  - Encoding of an office recording



Acoustic Scene Classification

Deep Learning-based Approaches

- Example 1: [McDonnel & Gao, 2020]
  - Based on ResNet architectures
  - Mel spectrogram split into low/high frequencies
  - Late fusion
  - Feature: Mel spectrogram + Δ + Δ Δ

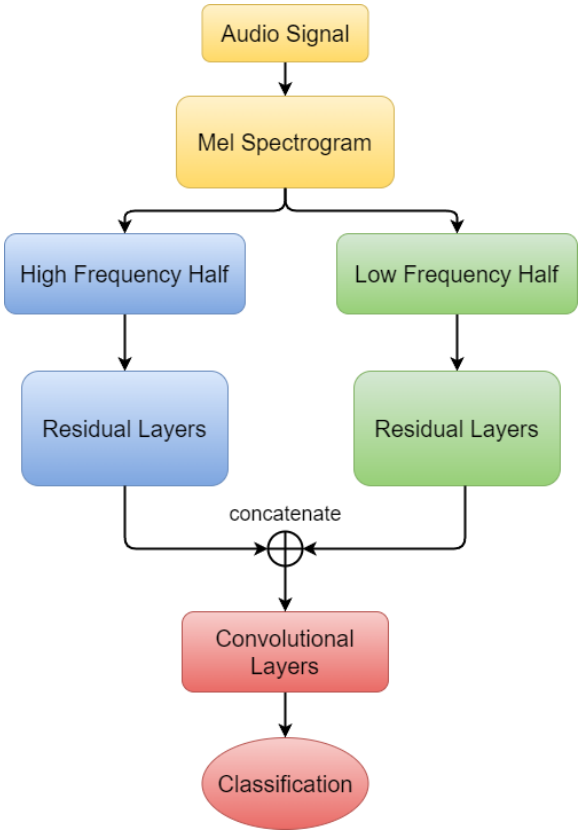


Fig-E3-4

Acoustic Scene Classification

Deep Learning-based Approaches

- Example 2: [Koutini et al. 2019]
  - Modifications of residual block (improved stability and robustness)

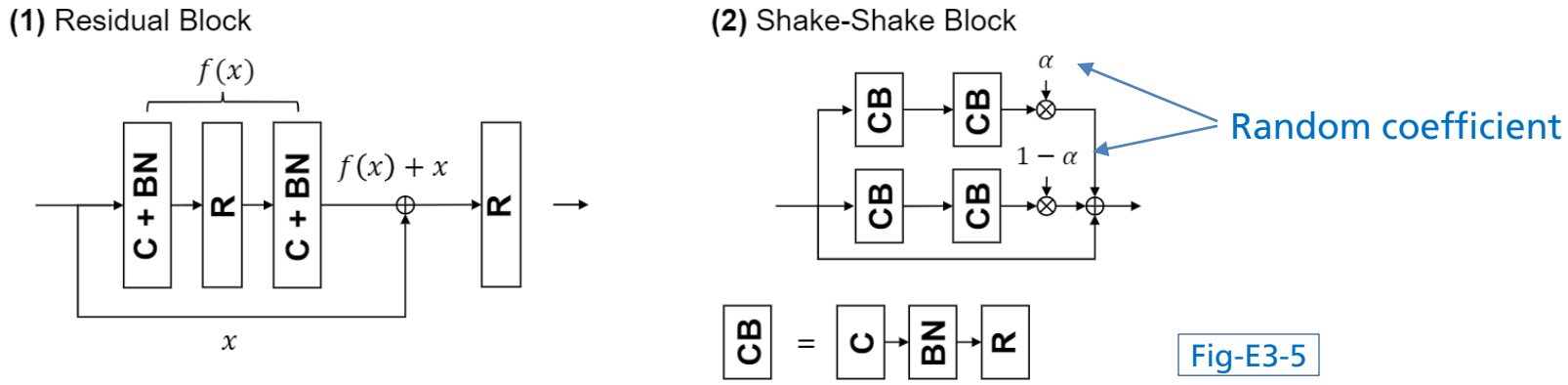


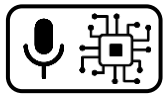
Fig-E3-5

  - Frequency-aware CNN
    - Additional channel with normalized frequency between 0 and 1

Acoustic Scene Classification

Domain Adaptation

- Domain shift differences in data distribution due to
    - Room acoustics (reverb, reflections)
    - Microphone characteristics (frequency response, directionality)
- Domain adaptation
    - Align source and target data distributions
        - Unsupervised: adversarial training [Gharib, 2018]
        - Supervised: transfer learning
- Approaches
    - Data augmentation
    - Data normalization [Johnson, 2020] [Latifi, 2023]



Acoustic Scene Classification

Domain Adaptation

- Domain adaptation (DA)
  - Unsupervised DA via adversarial training [Gharib, 2018]

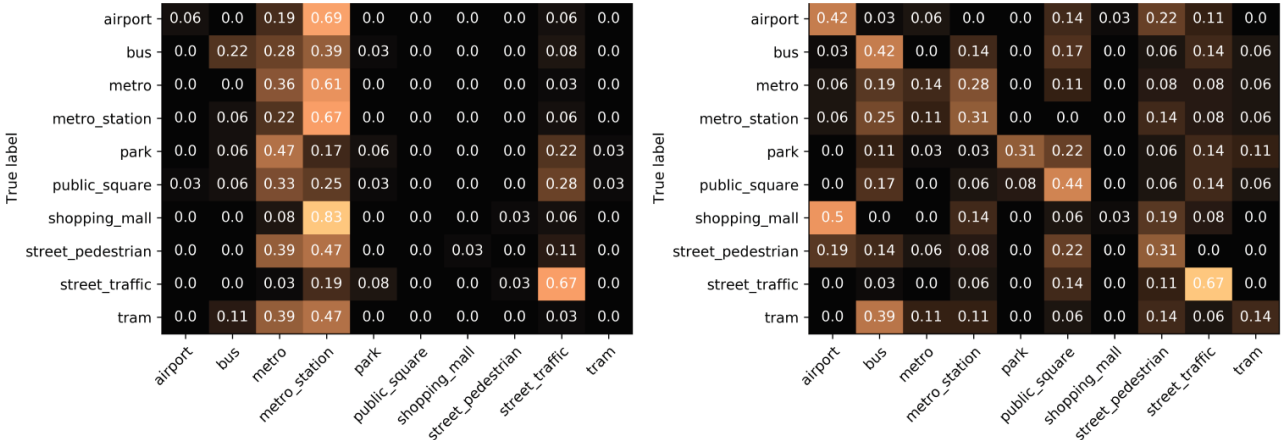


Fig-E3-6

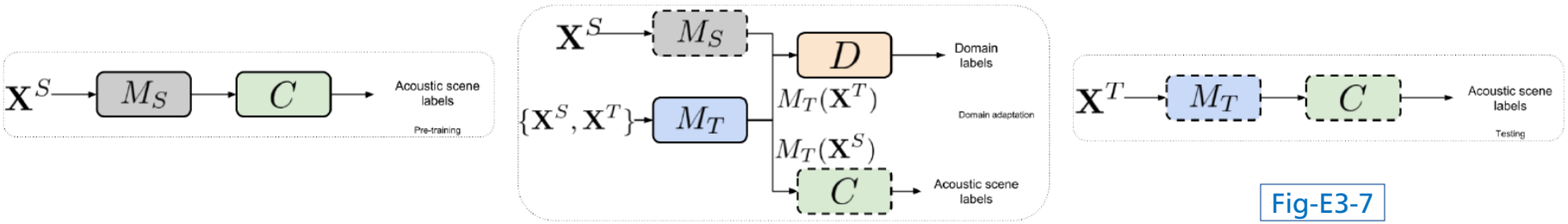


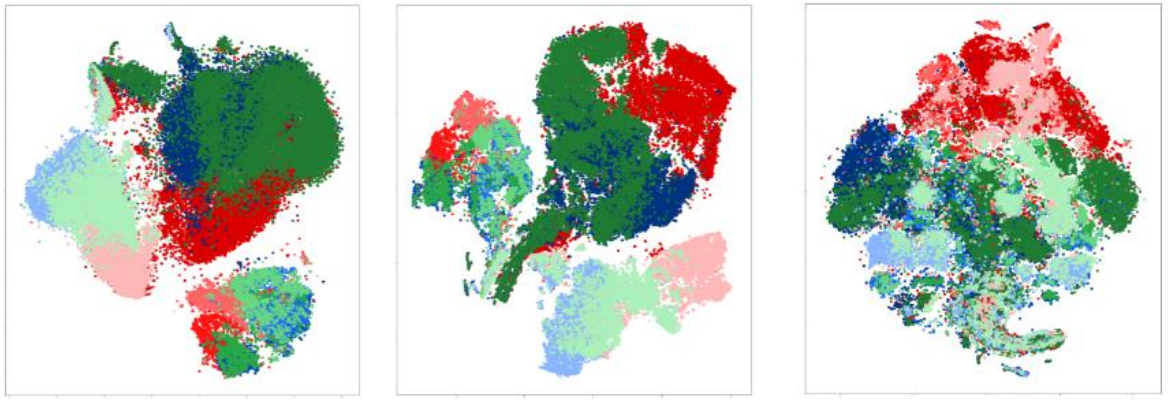
Fig-E3-7

Acoustic Scene Classification

Domain Adaptation

- Data normalization
  - Align source and target data distribution (zero mean & standard deviations) [Johnson, 2020]
  - Reduce domain shift

Metal ball surface classification (colors = classes, shadings = recordings)



(a) No Norm (b) Global Norm (c) Adaptive Norm

Fig-E3-8

Acoustic Scene Classification

Efficient Models

- Goals
  - Reduce model size – fewer parameters, less memory required
  - Reduce latency (inference time) / lower energy consumption

- Approaches ([Wang, 2021])
  - Model pruning
  - Identify & remove redundant connections / neurons

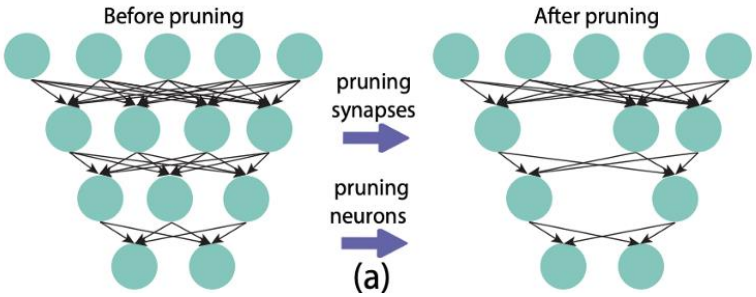


Fig-E3-9

Acoustic Scene Classification

Efficient Models

- Approaches
  - Quantization
    - Reduce numeric precision while minimize information loss
    - Ex.: 32-bit floating point -> 8-bit fixed point (256 values)
  - Reduce memory footprint of network weights
- Low-rank tensor decompositions
  - Replace (many) redundant filters by a linear combination of fewer filters
- Knowledge Distillation
  - Transfer knowledge from complex (teacher) to simpler (student) model

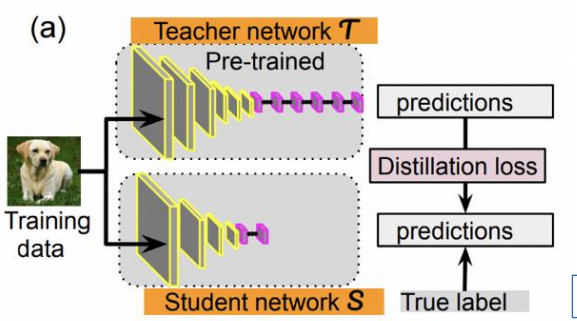


Fig-E3-10

Programming session

Fig-A2-13

References

Images

Fig-E2-1: [Virtanen, 2018], p. 267, Fig. 9.7

Fig-E2-2: https://images.theconversation.com/files/349387/original/file-20200724-15-ldrybi.jpg

Fig-E2-3: [Abeßer, 2024], p. 8, Fig. 2

Fig-E2-4: Zhiwei Liang, Final Presentation, Master Thesis “Self-Similarity Based Representations of Soundscape Recordings for Acoustic Scene Classification”, TU München (2023)

Fig-E2-5: Own

Fig-E2-6: [Gharib, 2018], p. 3., Fig. 2 (a) & (b)

Fig-E2-7: [Gharib, 2018], p. 2., Fig. 1

Fig-E2-8: [Johnson & Grollmisch, 2021], p. 82, Fig. 1

Fig-E2-9: https://miro.medium.com/max/955/1*C3rR1-qzZfgYE_QA7WvLOQ.png

Fig-E2-9: [Wang, 2021], p. 2, fig. 1 (a)

Fig-E2-10: https://dcase.community/images/tasks/challenge2019/task1_acoustic_scene_classification_openset.png

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Audio

Aud-E3-1: 16HPanskaTyllova_Terezie - 17-1_atmosphere of office.wav (2019) - CC0 License, https://freesound.org/people/16HPanskaTyllova_Terezie/sounds/497363