Machine Listening for Music and Sound Analysis

Lecture 5 - Environmental Sound Analysis 1

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https://machinelistening.github.io

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Overview

- Introduction
- Sound Event Detection
    - Introduction
    - Challenges & Related Tasks
    - Pipeline
    - Evaluation Metrics & Datasets
    - Data Augmentation
    - Methods
        - Traditional
        - Neural Network Based

Introduction
Motivation

- Sound carries information about our environment
- Challenging attempt to mimic the human‘s abilities
    - Environment perception
    - Context-awareness & localization of sound sources
    - Acoustic scene understanding
- Complementary sensory path to vision → multimodality
- Related to other content analysis domains (speech, music)

Introduction
Environmental Sounds (Recap)

- Sound sources
  - Nature, climate, humans, machines, etc.
- Sound characteristics
  - Structured or unstructured, stationary or non-stationary, repetitive or without any predictable nature
- Sound duration
  - From very short (gun shot, door knock, shouts) to very long and almost stationary (running machines , wind, rain)

AUD-1

Fig. 1

Fig. 2

Fig. 3

Introduction
Tasks / Categories

- Sound event detection (SED)
- Acoustic scene classification (ASC)
- Acoustic anomaly detection (AAD)

Sound Event Detection
Introduction

- Sound event detection → 2 simultaneous tasks
  - Segmentation (detection of temporal boundaries)
  - Classification (type of sound)
- Sound polyphony
  - Number of simultaneous sounds
  - Depends on the acoustic scene composition & sound sources

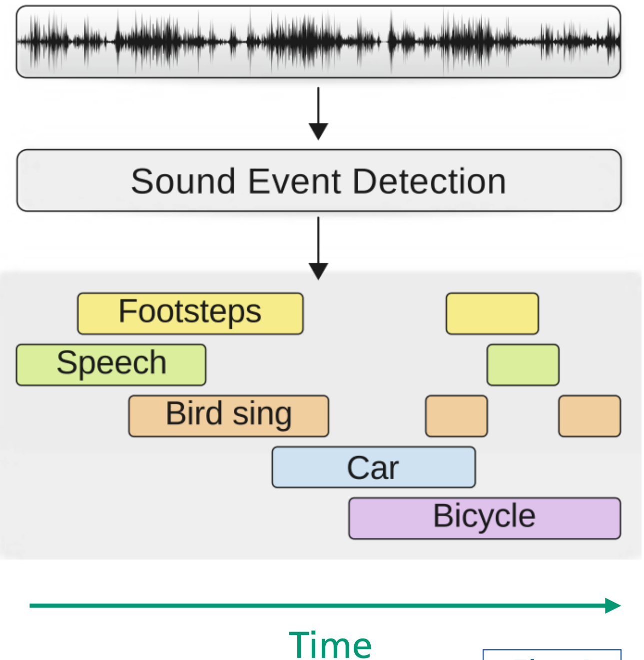

Fig. 4

Sound Event Detection
Introduction

- USM-SED dataset
  [Abeßer, 2021]

Polyphony = 6

AUD-6

Polyphony = 4

AUD-7

Polyphony = 2

AUD-8

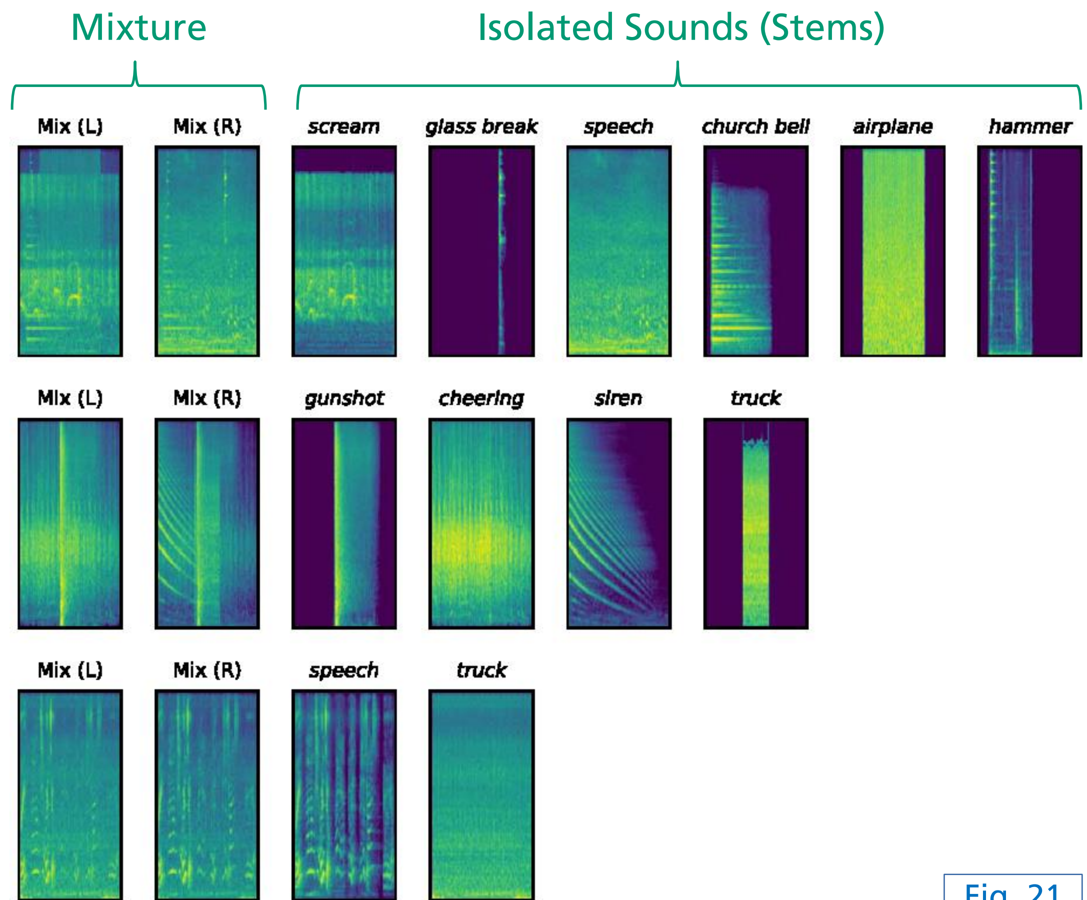

Fig. 21

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Sound Event Detection
Introduction

- Sound source categories
  - Humans, animals, vehicles, tools, machines, climate, …
- Hierarchies of sounds (e.g., urban sounds)
  - Based on origin & characteristics

AUD-2

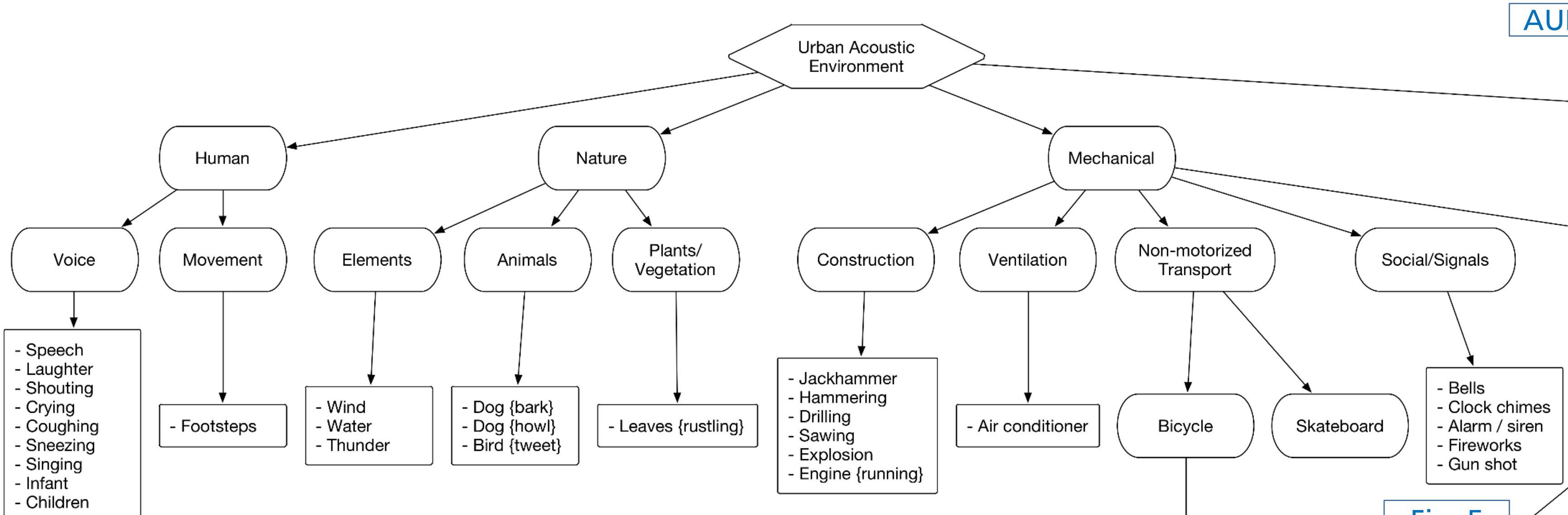

Fig. 5

Sound Event Detection
Challenges

- Sound characteristics
  - Short transients, noise-like signals, harmonic / inharmonic signals
- Sound durations
  - Short (gun shot, door knock) → long / stationary (machines, wind)
- Ill-defined temporal boundaries
  - Complicates annotation & detection

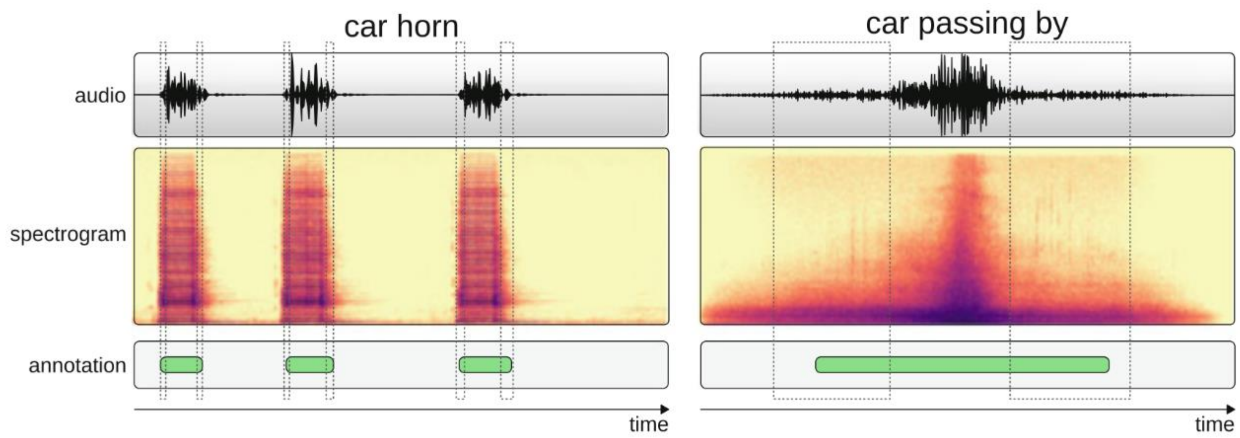

Fig. 6

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Sound Event Detection
Challenges

- Sound appear in the foreground & background
  - depending on relative sound source position
- Non-local / sparse energy distribution
  - Fundamental frequency & overtones

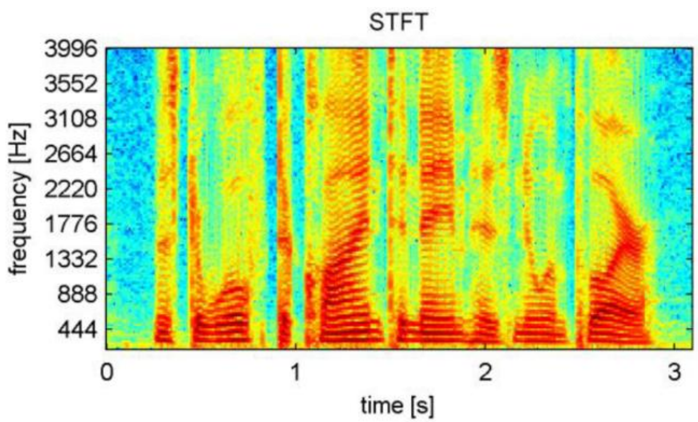


Fig. 7

- Sounds are “transparent“
  - Phase-dependent overlap, possible cancelations

Sound Event Detection
Related tasks

- Sound event localization & tracking
  - Multichannel audio recordings (e.g., first-order ambisonic microphones)
  - Estimate direction-of-arrival (DOA) & track source movement

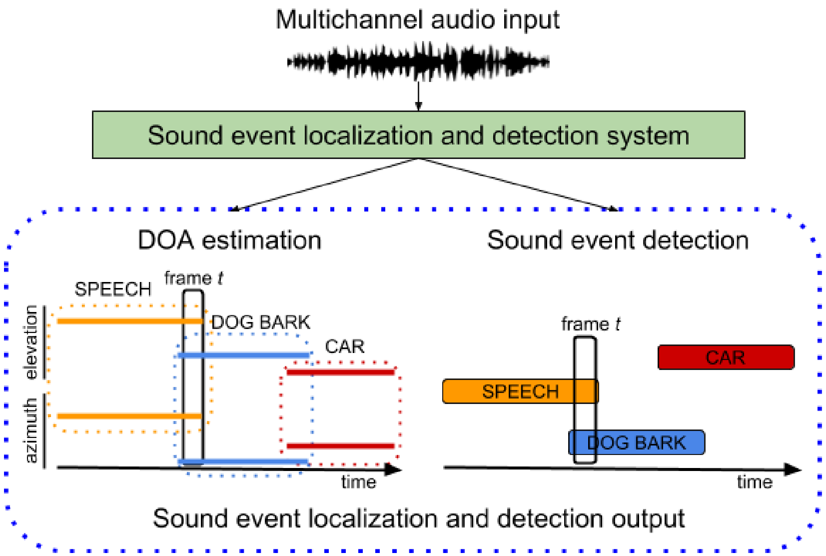


Fig. 14

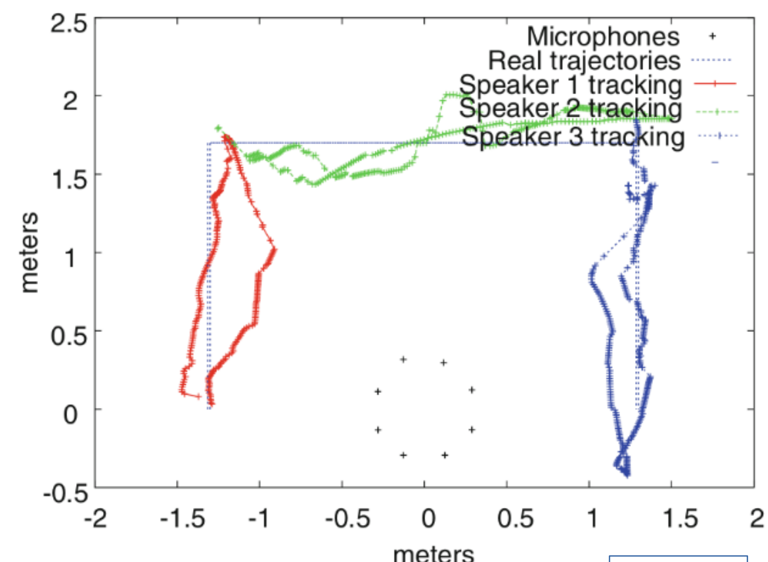


Fig. 15

Sound Event Detection
Related tasks

- Source separation
  - Prior to sound event detection
- Chicken-egg problem
  - Alternative: sound-informed source-separation

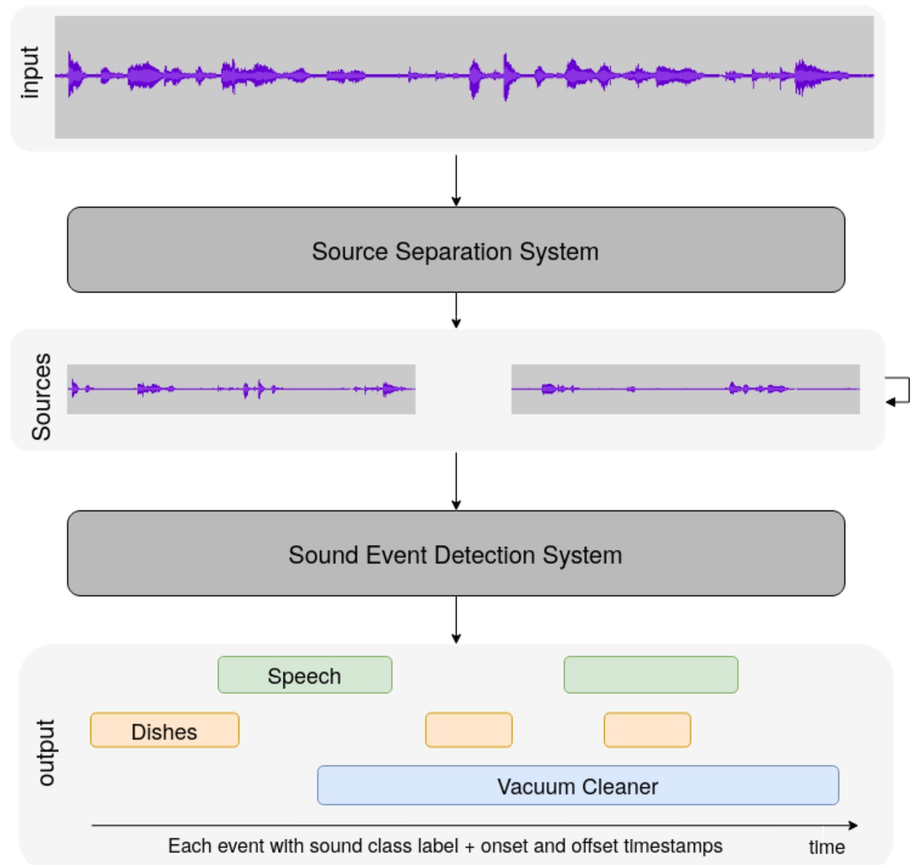


Fig. 16

Sound Event Detection
Pipeline

- Supervised learning pipeline
    - Feature extraction & pre-processing
    - Label encoding
    - Acoustic modeling

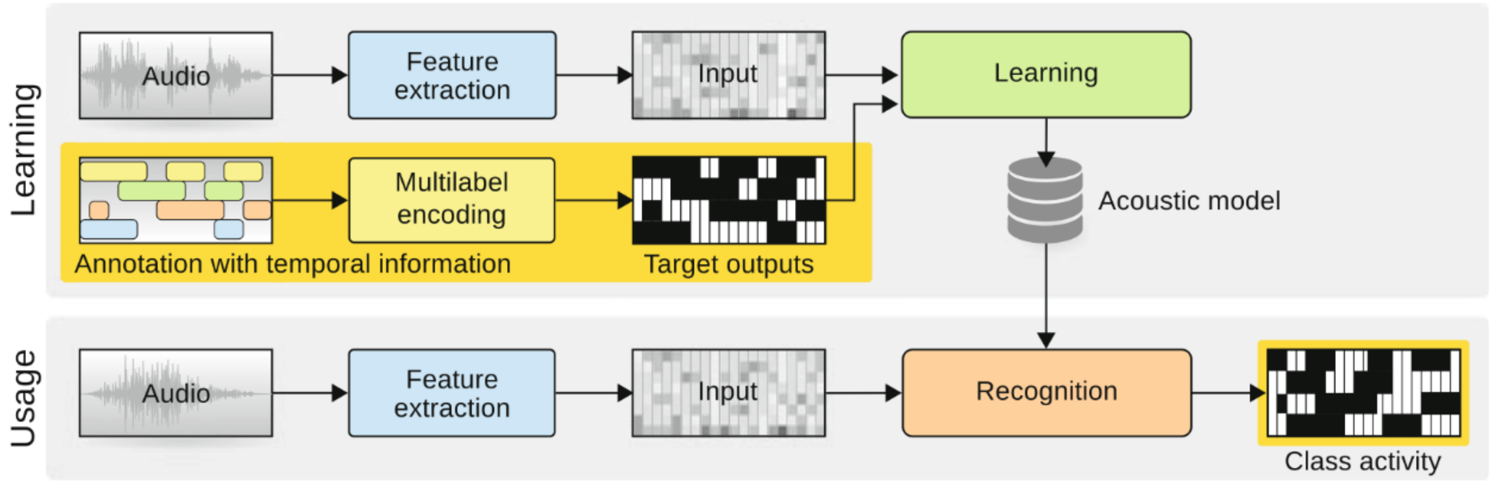
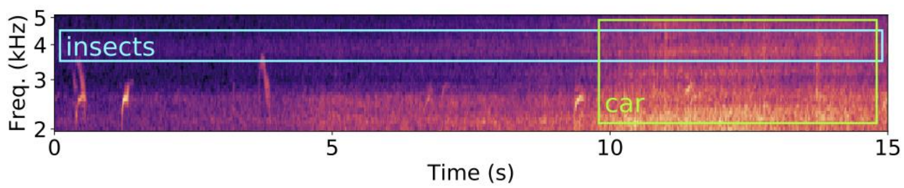


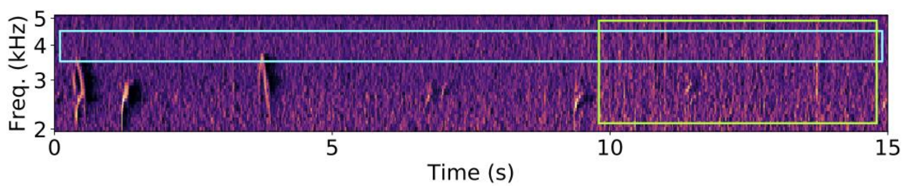
Fig. 8

Sound Event Detection
Pipeline

- Feature extraction
  - 1D features (audio samples) → "end-to-end learning"
  - 2D features (mel-spectrogram, STFT)
- Feature pre-processing
  - Log-magnitude scaling
  - Per-channel energy (PCEN) [Lostanlen, 2019]
    - Dynamic range compression
    - Adaptive gain control
    - Suppresses stationary (background) noise



(a) Logarithmic transformation.



(b) Per-channel energy normalization (PCEN).

Fig. 9

Sound Event Detection
Pipeline

- Annotation
  - Quality of “ground truth”? (limited agreement / reliability)
  - Different granularities
    - Tagging / Global level (“weak” labels) → cheap
    - Event-level (“strong" labels) → expensive

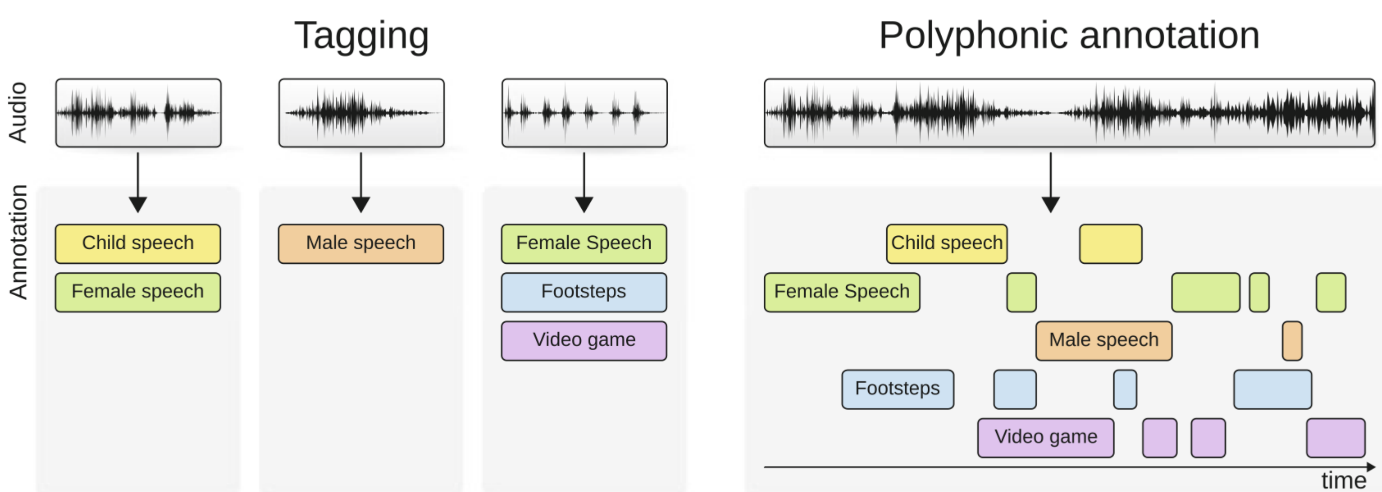


Fig. 10

Sound Event Detection
Pipeline

- Label encoding
  - Binarized sound activity (0/1)
    - Multilabel classification
    - 1 (independent) binary detector per class
  - Temporal resolution (duration of each annotated time frame)

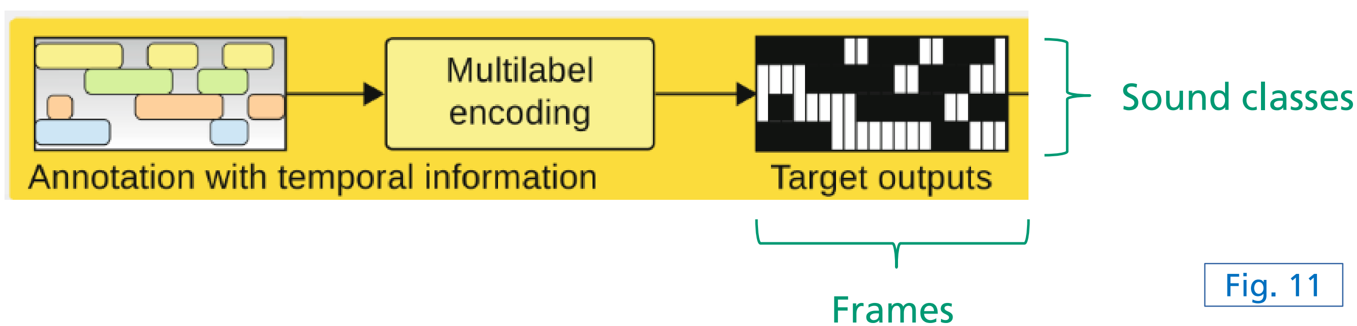
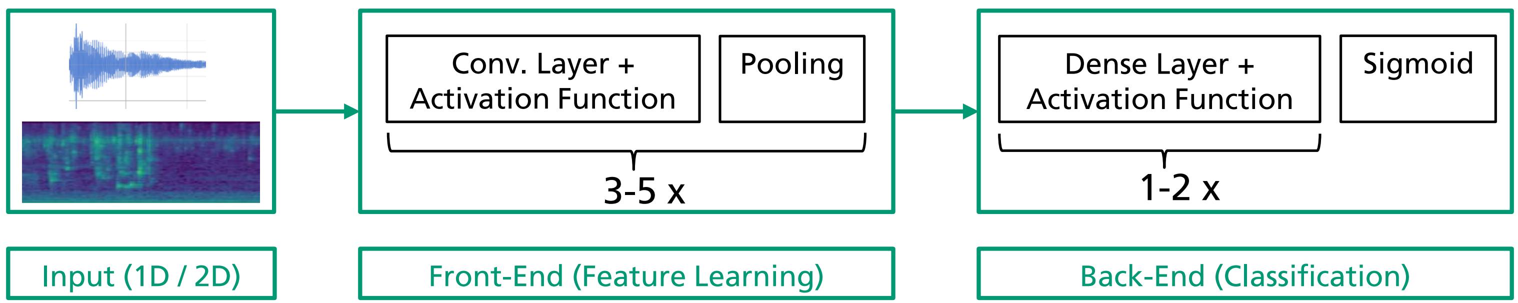


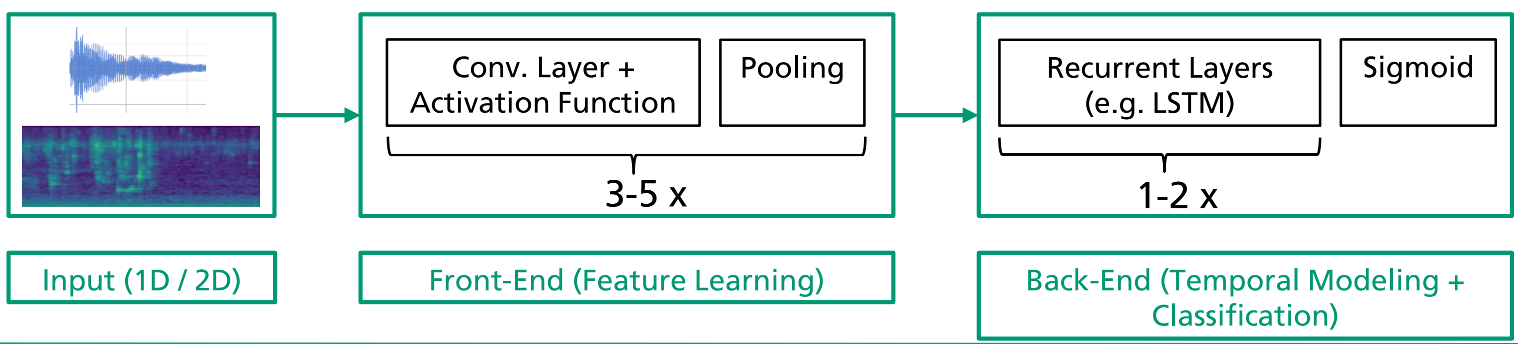
Fig. 11

Sound Event Detection
Pipeline

- Typical neural network architectures
  - CNN



  - CRNN



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Sound Event Detection
Pipeline

- Evaluate SED → binary classification results on a frame-level
- Compare reference with predictions
- Count TP/FN/FP → aggregate over time → compute metrics

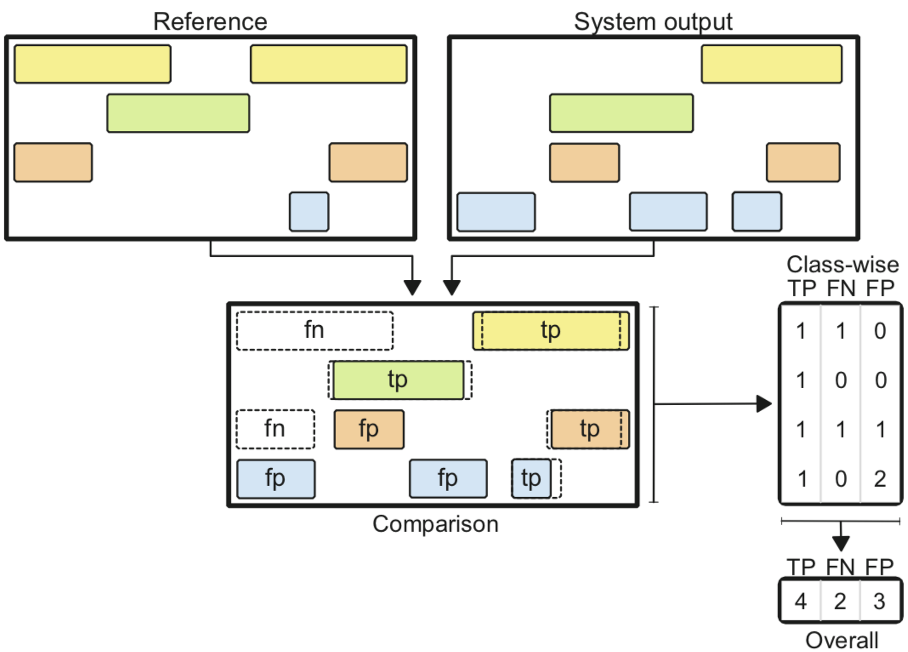

Fig. 13

Sound Event Detection
Evaluation Metrics

- Recap: Binary classification evaluation
  - True/false positives (TP/FP)
  - True/false negatives (TN/FN)
  - Metrics
    - Precision
    - Recall
    - Accuracy
    - F-score

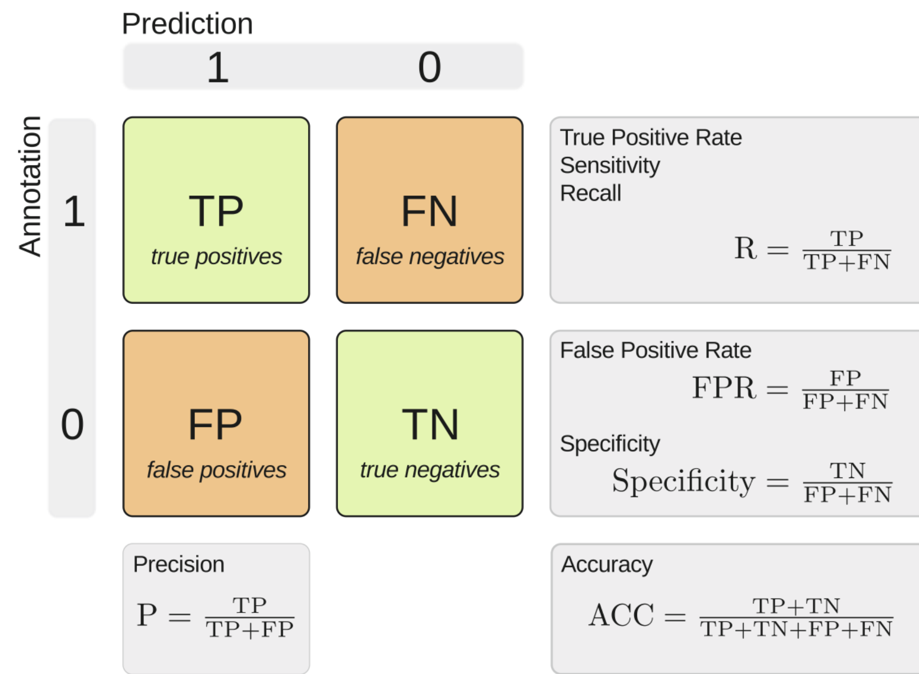

Fig. 12

Sound Event Detection
Data Augmentation

- Data Augmentation
  - Increases amount / variability of training data
  - Improves model generalization towards unseen data
- Methods
  - Audio signal transformations
    - Time stretching, pitch shifting, dynamic range compression
  - SpecAugment [Park, 2019]
    - Temporal warping (1)
    - Block-wise masking (2)

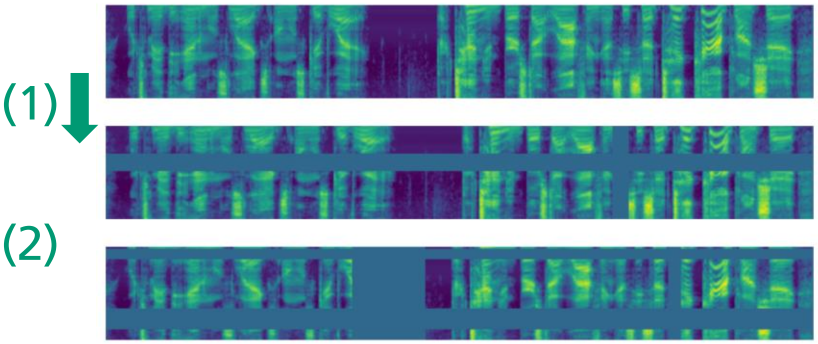

Fig. 19

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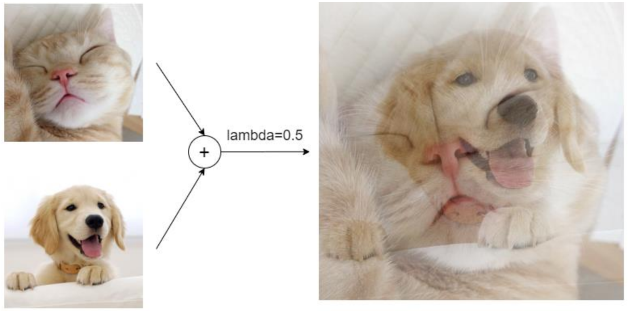
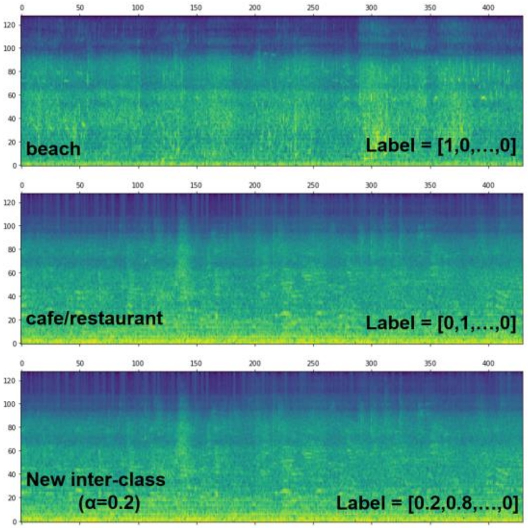
Sound Event Detection
Data Augmentation

- Methods
  - Mix-up data augmentation [Zhang, 2018]
    - Simulate sound mixtures
    - Mix two data instances with random mixing ratio

$$x = \alpha \cdot x_1 + (1 - \alpha) \cdot x_2$$
$$y = \alpha \cdot y_1 + (1 - \alpha) \cdot y_2$$



Computer Vision Fig. 17



Machine Listening Fig. 18

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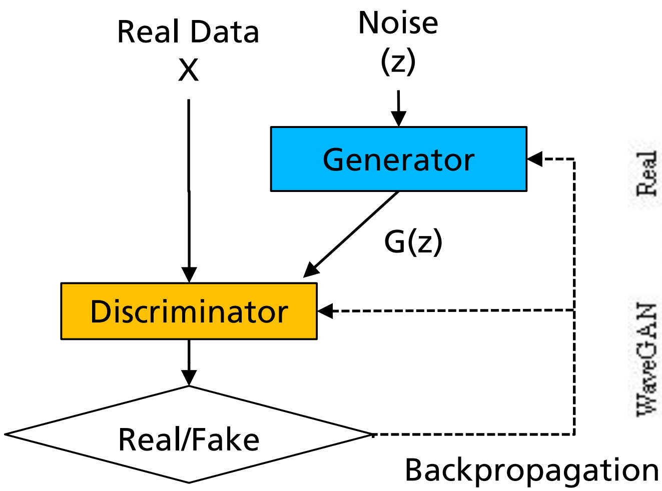
Sound Event Detection
Data Augmentation

- Methods
  - Data Synthesis
    - WaveGAN [Donahue, 2019]
      - Waveform synthesis with (conditional) Generative Adversarial Networks (GAN)

Training (GANs)



Synthesis Examples (Spectrograms)

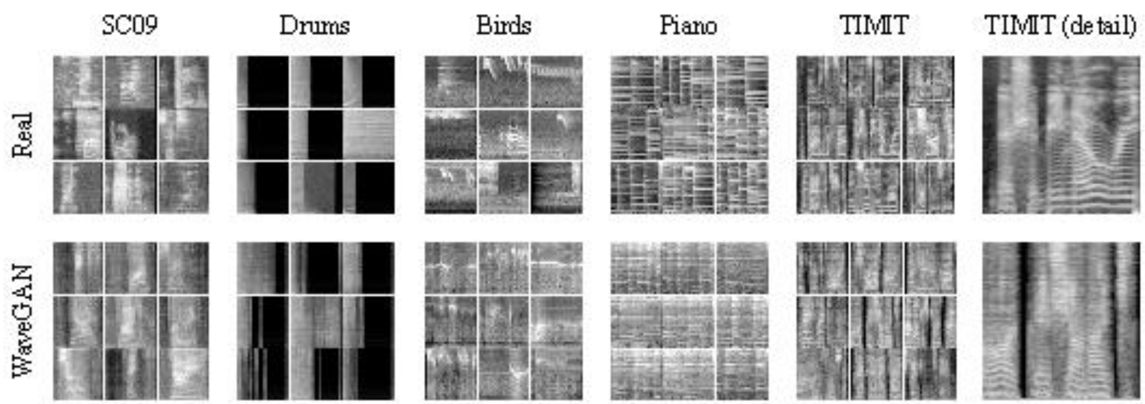


Fig. 20

Sound Event Detection
Novel Methods

- VGG-style CNN [Sakashita, 2018]
  - Pairs of convolutional layers before max pooling
  - Final classification layers (dense)

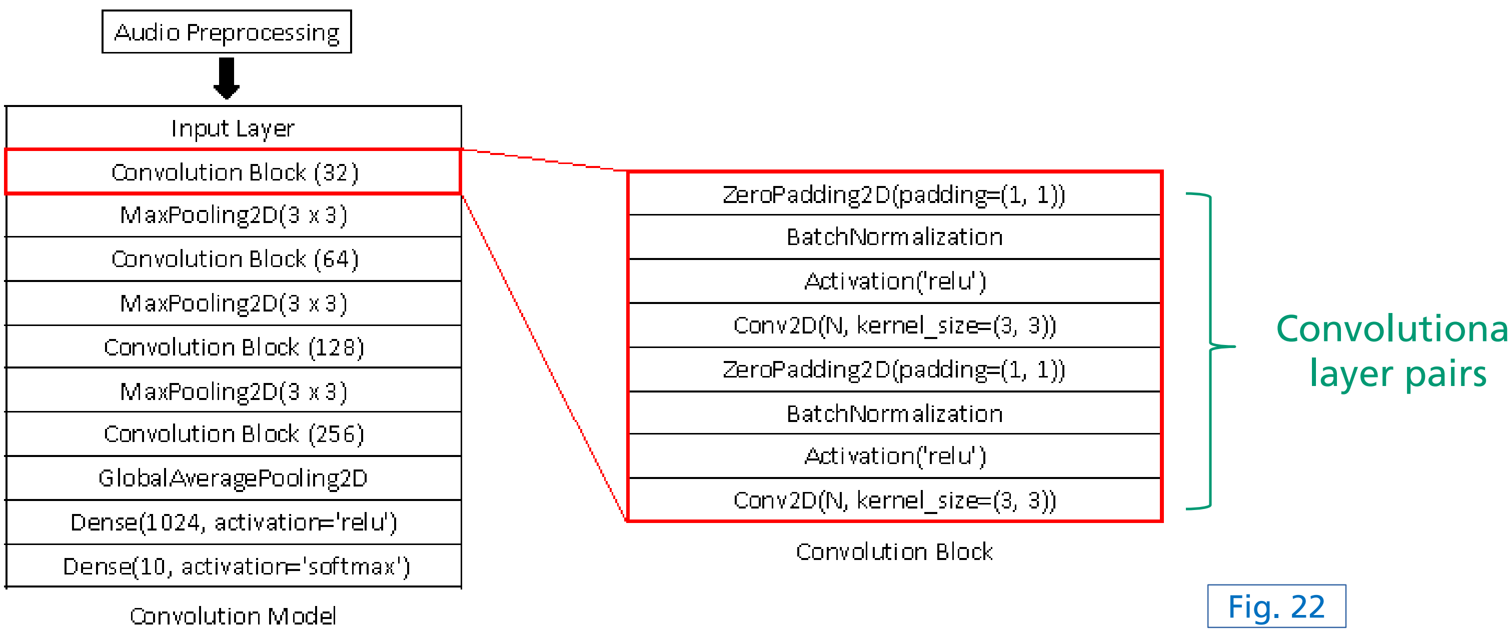
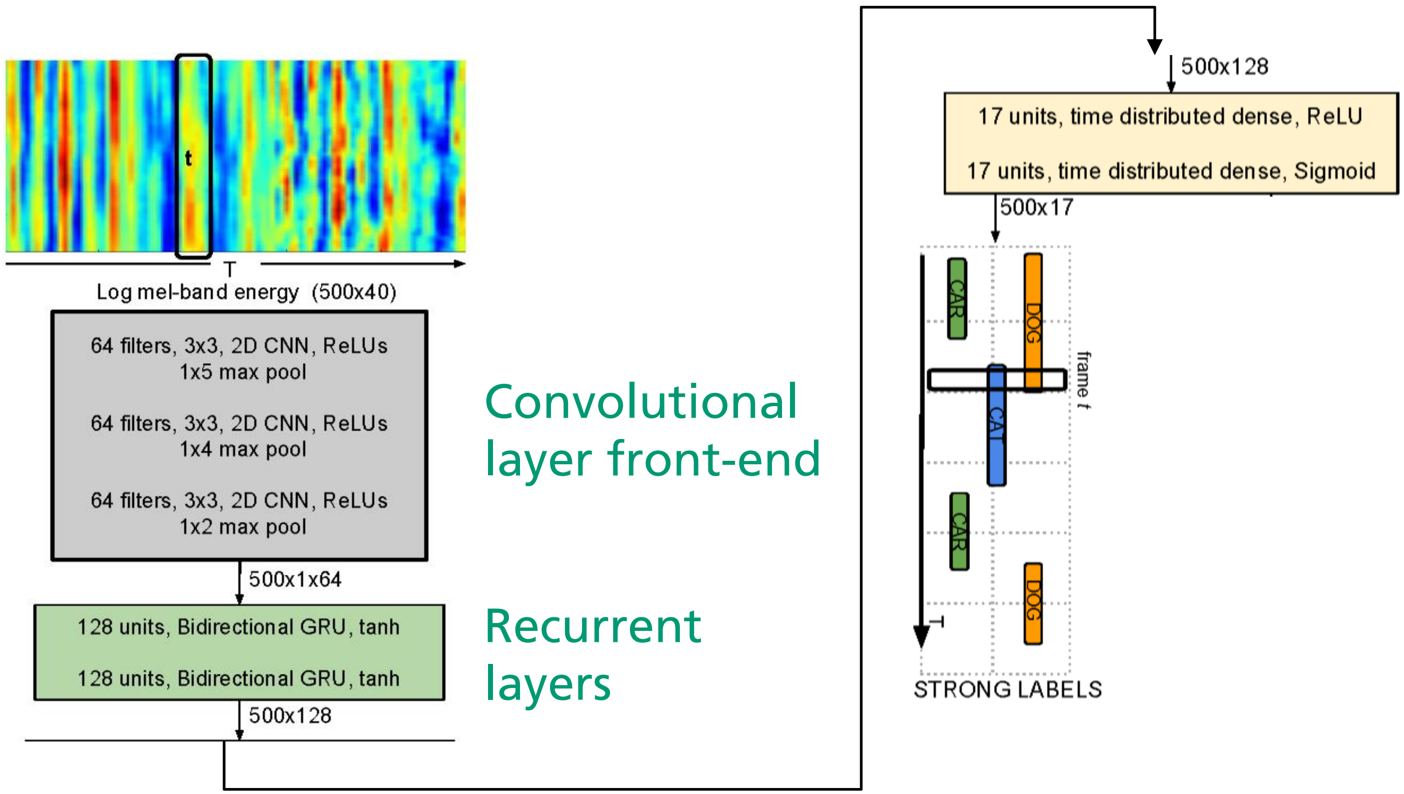


Fig. 22

Sound Event Detection
Novel Methods

- CRNN [Adavanne, 2017]



Convolutional layer front-end

Recurrent layers

Dense layers

Frame-wise multilabel predictions

Fig. 23

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Sound Event Detection
Novel Methods

- CRNN + Attention [Xu, Kong, et al., 2018]
  - Gated Linear Units (GLU) replace ReLU
    - Element-wise gating of each time-frequency bin
  - Similar gating after RNN layer for event localization

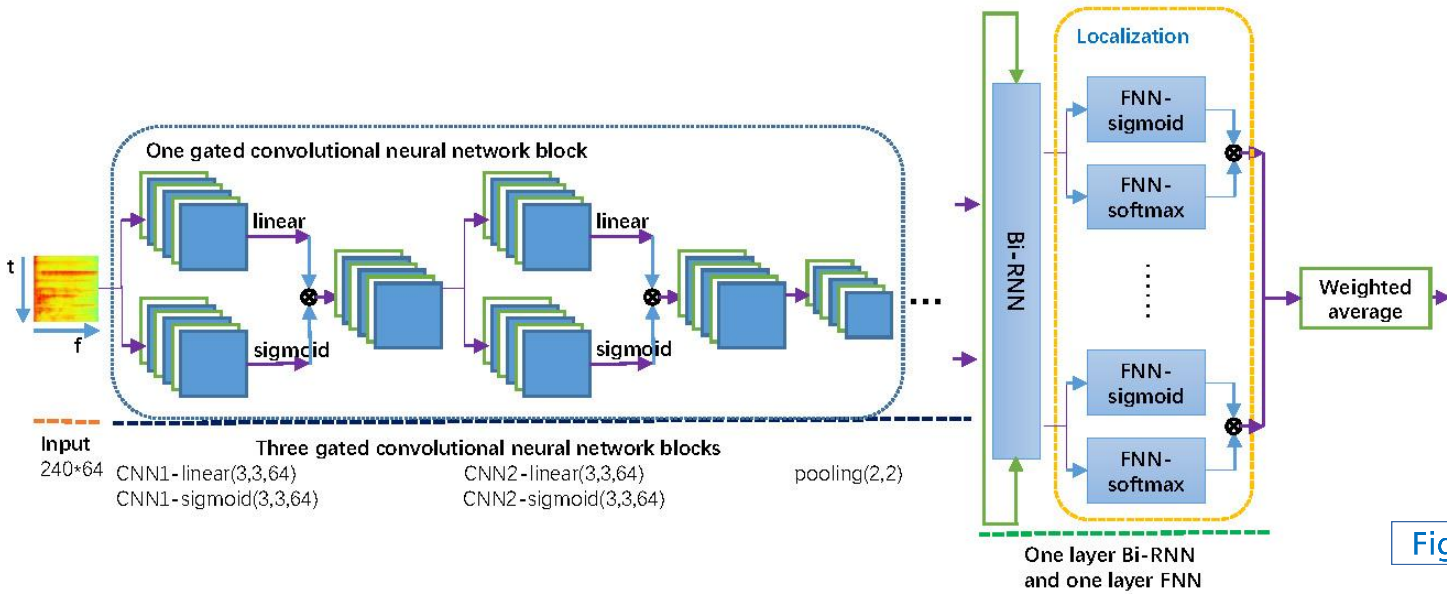

Fig. 24

Sound Event Detection
Novel Methods

- Alternative Architectures
  - ResNet
    - [He, 2015]
  - MobileNetV2
    - [Sandler, 2018]

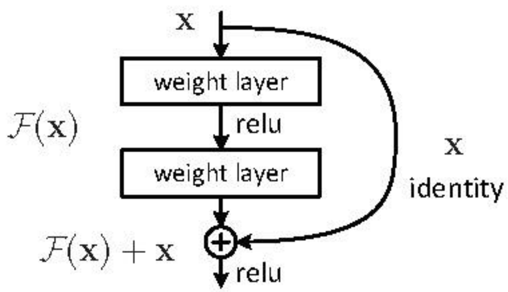

Fig. 25

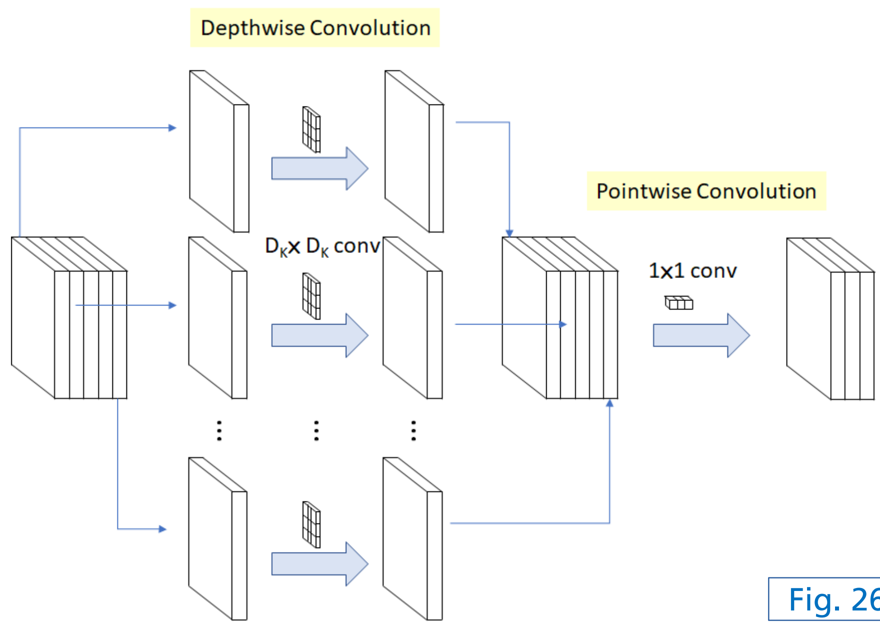

Fig. 26

Summary

- Introduction
- Sound Event Detection
    - Introduction
    - Challenges & Related Tasks
    - Pipeline
    - Evaluation Metrics & Datasets
    - Data Augmentation
    - Methods
        - Traditional
        - Neural Network Based

References

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Xu, K., Feng, D., Mi, H., Zhu, B., Wang, D., Zhang, L., … Liu, S. (2018). Mixup-Based Acoustic Scene Classification Using Multi-Channel Convolutional Neural Network. *Proceedings of the Pacific Rim Conference on Multimedia (PCM)*, 14–23. Hefei, China.

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Images

Fig. 1: https://ccsearch-dev.creativecommons.org/photos/39451123-ee45-4ec3-ad8d-b42d856bca06

Fig. 2: https://ccsearch-dev.creativecommons.org/photos/c69d3b07-76bd-43e2-a44e-8742edc8447a

Fig. 3: https://ccsearch-dev.creativecommons.org/photos/ab3062ab-fe0f-420d-b93d-7451db166b4e

Fig. 4: [Virtanen, 2018], p. 15, Fig. 2.1

Fig. 5: https://urbansounddataset.weebly.com/uploads/4/3/9/4/4394963/3427002_orig.png

Fig. 6: [Virtanen, 2018], p. 157, Fig. 6.3

Fig. 7: https://towardsdatascience.com/whats-wrong-with-spectrograms-and-cnns-for-audio-processing-311377d7ccd

Fig. 8: Virtanen et al., Computational Analysis of Sound Scenes and Events, p. 31, Fig. 2.11

Fig. 9: [Lostanlen, 2019], p. 1, Fig. 1

Fig. 10: [Virtanen, 2018], p. 154, Fig. 6.2

Fig. 11: [Virtanen, 2018], p. 31, Fig. 2.11 (excerpt)

Fig. 12: [Virtanen, 2018], p. 170, Fig. 6.7

Fig. 13: [Virtanen, 2018], p. 169, Fig. 6.6

Fig. 14: http://dcase.community/challenge2019/task-sound-event-localization-and-detection, Fig. 1

Images

Fig. 15: [Virtanen, 2018] , p. 267, Fig. 9.7

Fig. 16: http://dcase.community/challenge2020/task-sound-event-detection-and-separation-in-domestic-environments, Fig. 2

Fig. 17: https://miro.medium.com/max/955/1*XqyD5OE47AdqeR6KeMg9FQ.png

Fig. 18: [Xu, Feng, et al., 2018], p. 17, Fig. 2

Fig. 19: [Park, 2019], p. 2614, Fig. 2

Fig. 20: [Donahue, 2019], p. 5, Fig. 4

Fig. 21: [Abeßer, 2021], p. 3, Fig. 2

Fig. 22: [Sakashita, 2018], p. 3, Fig. 3

Fig. 23: [Adavanne, 2017], p. 2, Fig. 1

Fig. 24: [Xu, Kong, et al., 2018], p. 2, Fig. 1

Fig. 24: [He, 2015], p. 2, Fig. 2

Fig. 25: https://miro.medium.com/max/1400/1*Voah8cvrs7gnTDf6acRvDw.png

Sounds

AUD-1: https://freesound.org/people/{InspectorJ/sounds/416529, prometheus888/sounds/458461, MrAuralization/sounds/317361}

AUD-2: https://freesound.org/people/G_M_D_THREE/sounds/424404/

AUD-3: https://freesound.org/people/IFartInUrGeneralDirection/sounds/96195/

AUD-4: https://freesound.org/people/InspectorJ/sounds/400860/

AUD-5: https://freesound.org/people/Simon%20Spiers/sounds/516876/

AUD-6: USM-SED dataset [Abeßer, 2021], Evaluation Set, Sound ID 2417

AUD-7: USM-SED dataset [Abeßer, 2021], Evaluation Set, Sound ID 1930

AUD-8: USM-SED dataset [Abeßer, 2021], Evaluation Set, Sound ID 339

Thank you!

- Any questions?

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