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

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Introduction

Motivation

- Sound carries information about our environment
- Challenging attempt to mimic the human‘s abilities

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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

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)

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Introduction

Environmental Sounds (Recap)

- Sound sources
  - Nature, climate, humans, machines, etc.

AUD-1

Fig. 1

Fig. 2

Fig. 3

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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

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Introduction

Tasks / Categories

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

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Sound Event Detection

Introduction

- Sound event detection → 2 simultaneous tasks
    - Segmentation (detection of temporal boundaries)
    - Classification (type of sound)

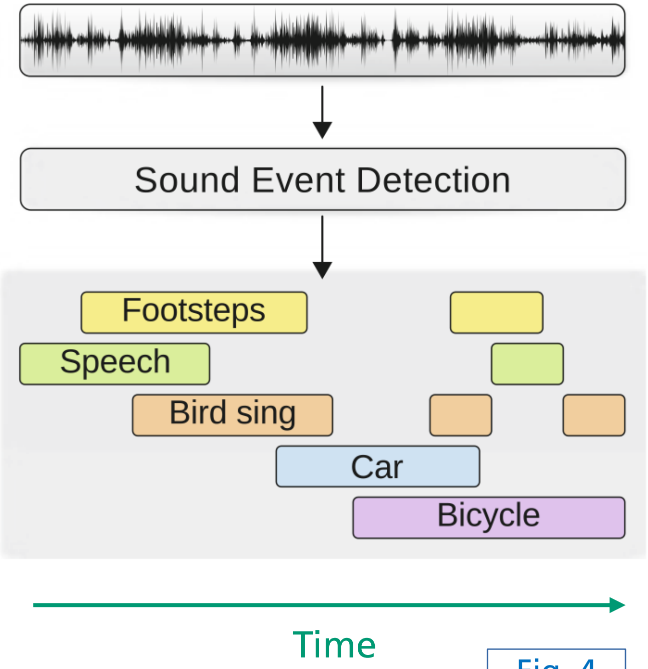

Fig. 4

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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

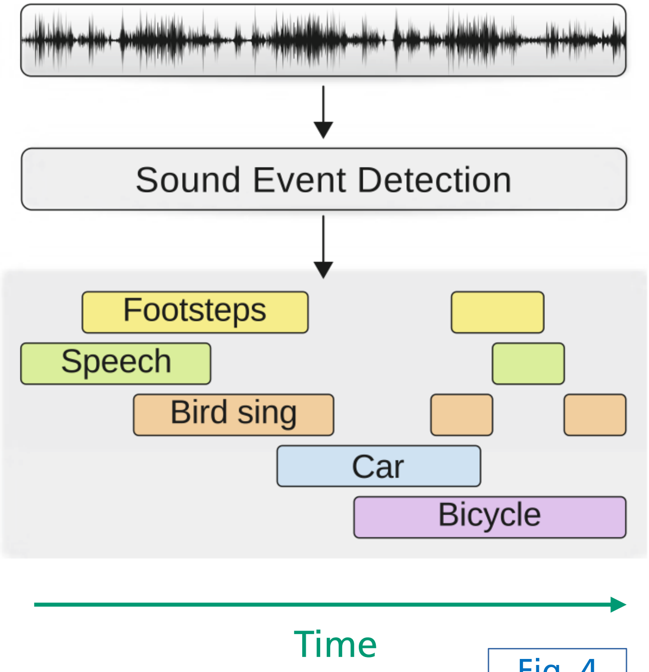

Fig. 4

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Sound Event Detection

Introduction

- USM dataset [Abeßer, 2022]

Polyphony = 6

AUD-6

Polyphony = 4

AUD-7

Polyphony = 2

AUD-8

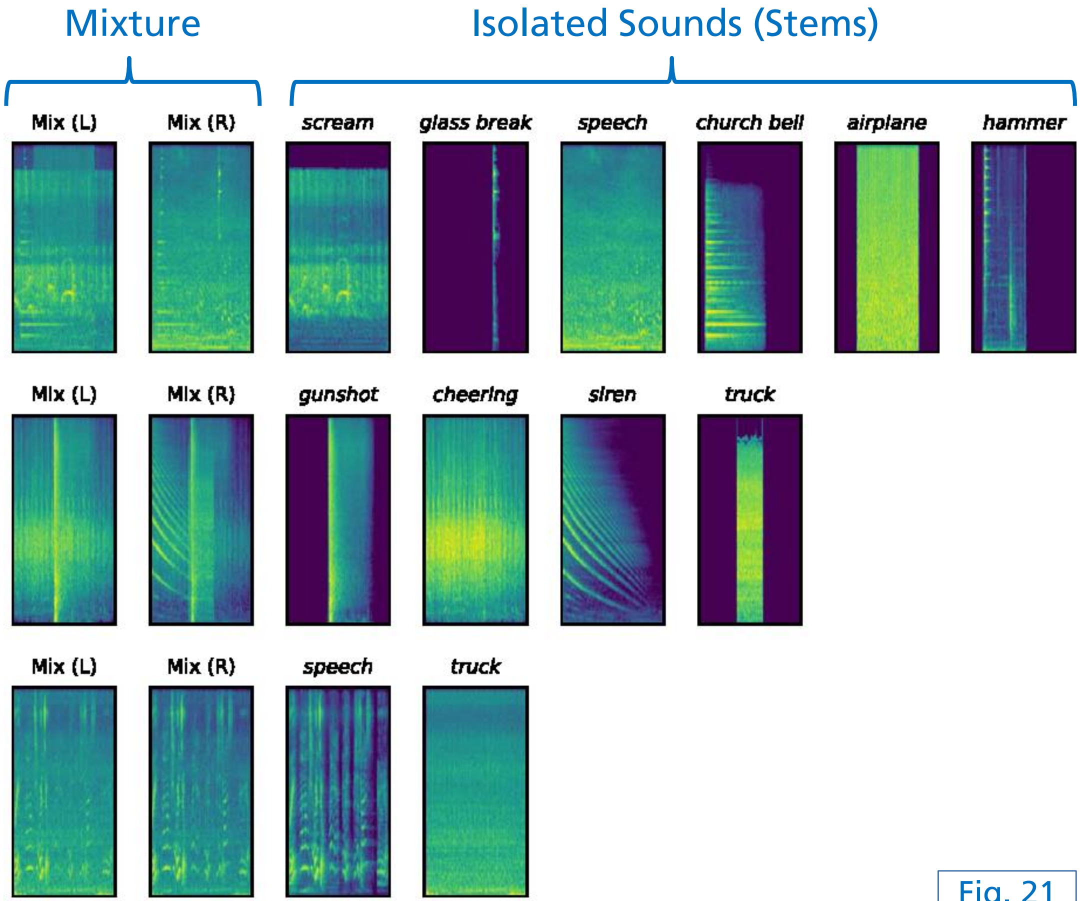

Fig. 21

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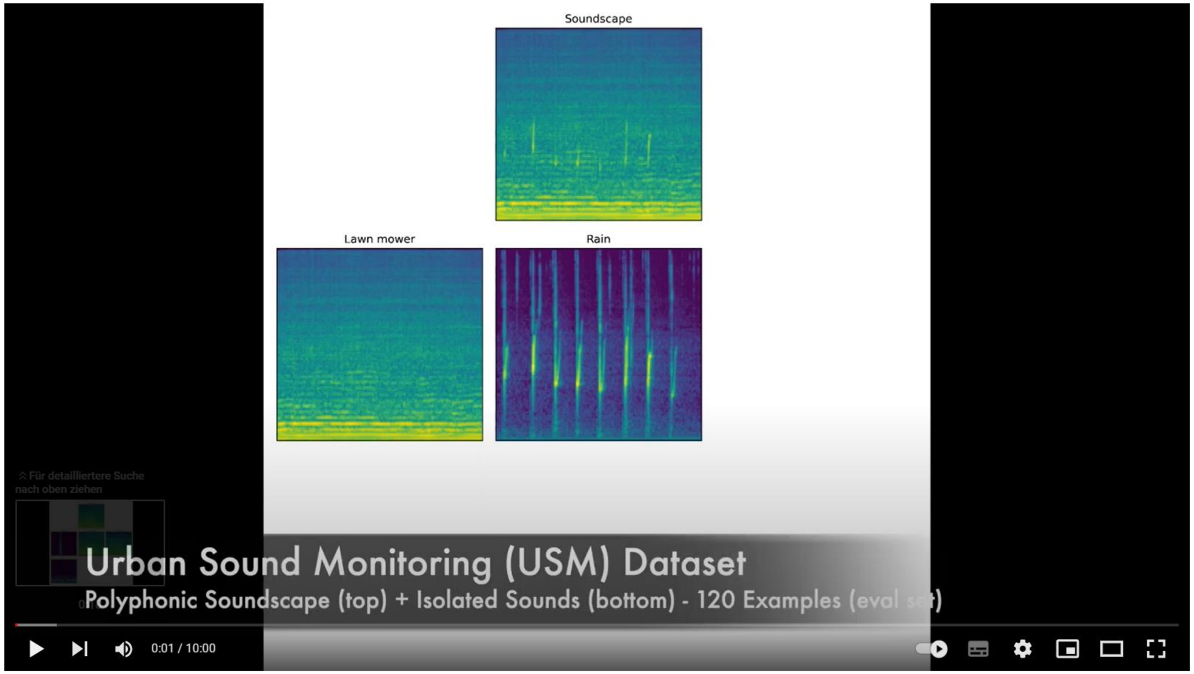
Sound Event Detection

Introduction

- USM dataset [Abeßer, 2022]

Demo-Video



Urban Sound Monitoring (USM) Dataset

Polyphonic Soundscape (top) + Isolated Sounds (bottom) - 120 Examples (eval set)

Demo of the Urban Sound Monitoring (USM) Dataset for Polyphonic Sound Event Tagging

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Sound Event Detection
Introduction

- Sound source categories
    - Humans, animals, vehicles, tools, machines, climate, …
- Sound hierarchies
    - Based on origin & characteristics

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Sound Event Detection
Introduction

- Sound source categories
  - Humans, animals, vehicles, tools, machines, climate, …
- Sound hierarchies
  - Based on origin & characteristics

AUD-2

Example: Urban Sounds

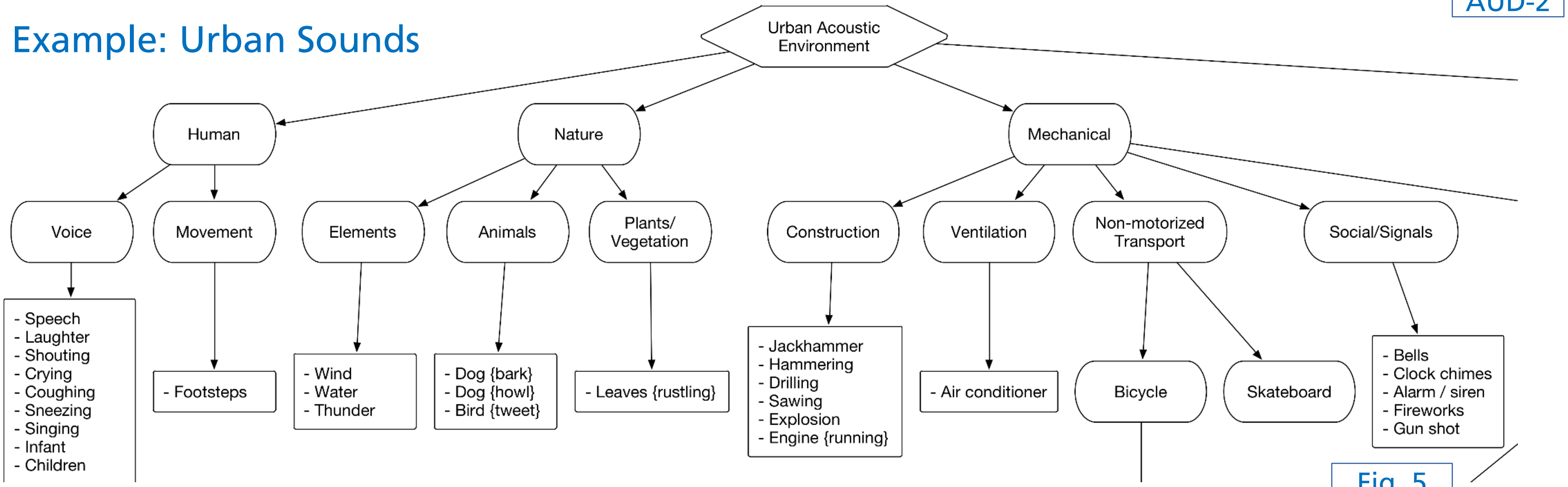

Fig. 5

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Sound Event Detection

Challenges

- Sound characteristics
    - Short transients, noise-like signals, harmonic / inharmonic signals

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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)

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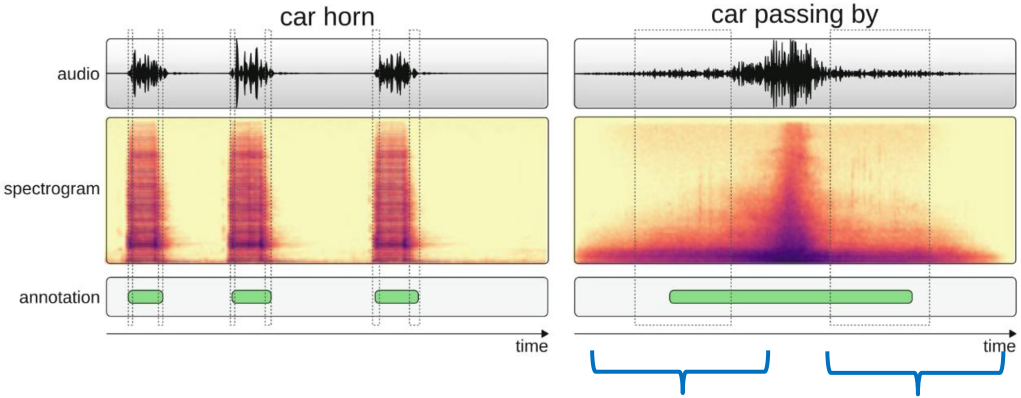
Sound Event Detection
Challenges

- 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



Ill-defined

Fig. 6

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Sound Event Detection
Challenges

- Sound appear in the foreground & background
    - depending on relative sound source position

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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

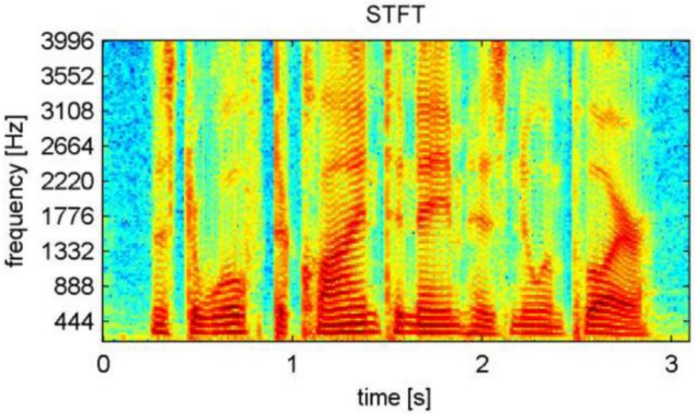

Fig. 7

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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

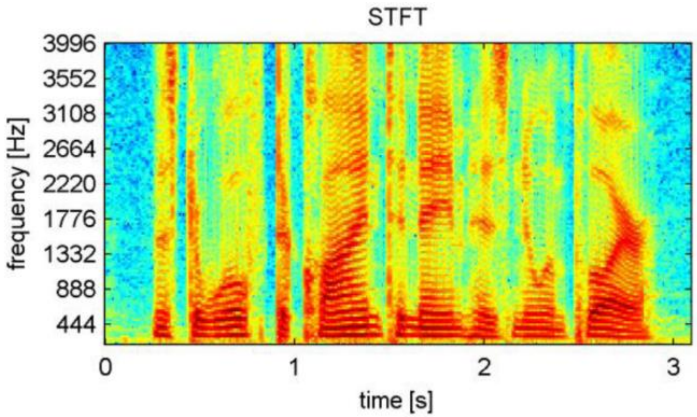

Fig. 7

- Sounds overlap / visual objects occlude
    - Possible phase cancellation

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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

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Sound Event Detection

Related tasks

- Sound event localization & tracking
  - Multichannel audio recordings (e.g., first-order ambisonic microphones)
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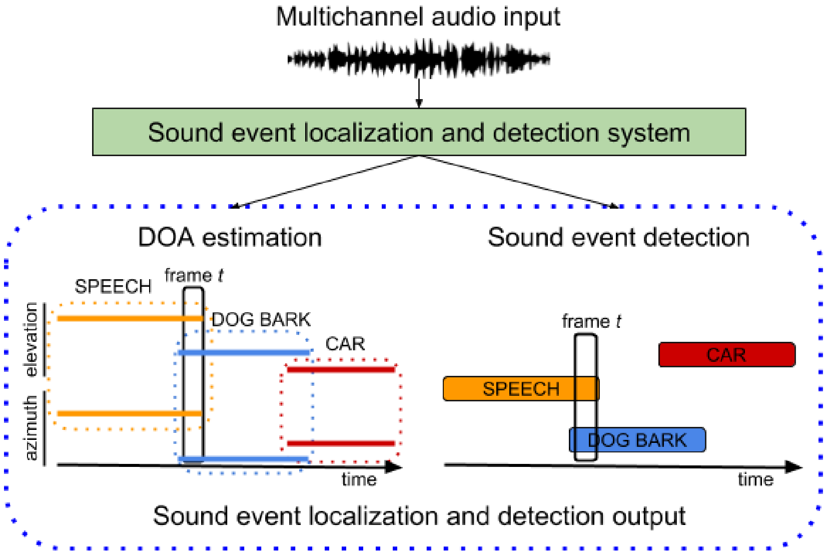

Fig. 14

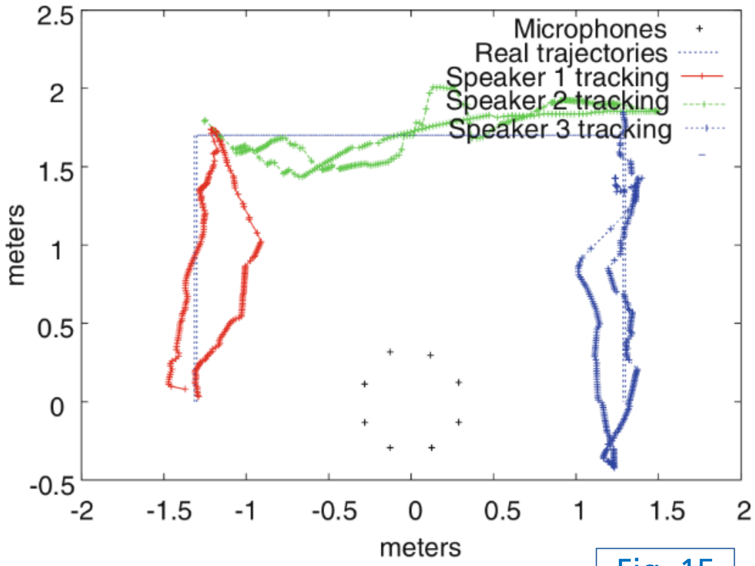

Fig. 15

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Sound Event Detection

Related tasks

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

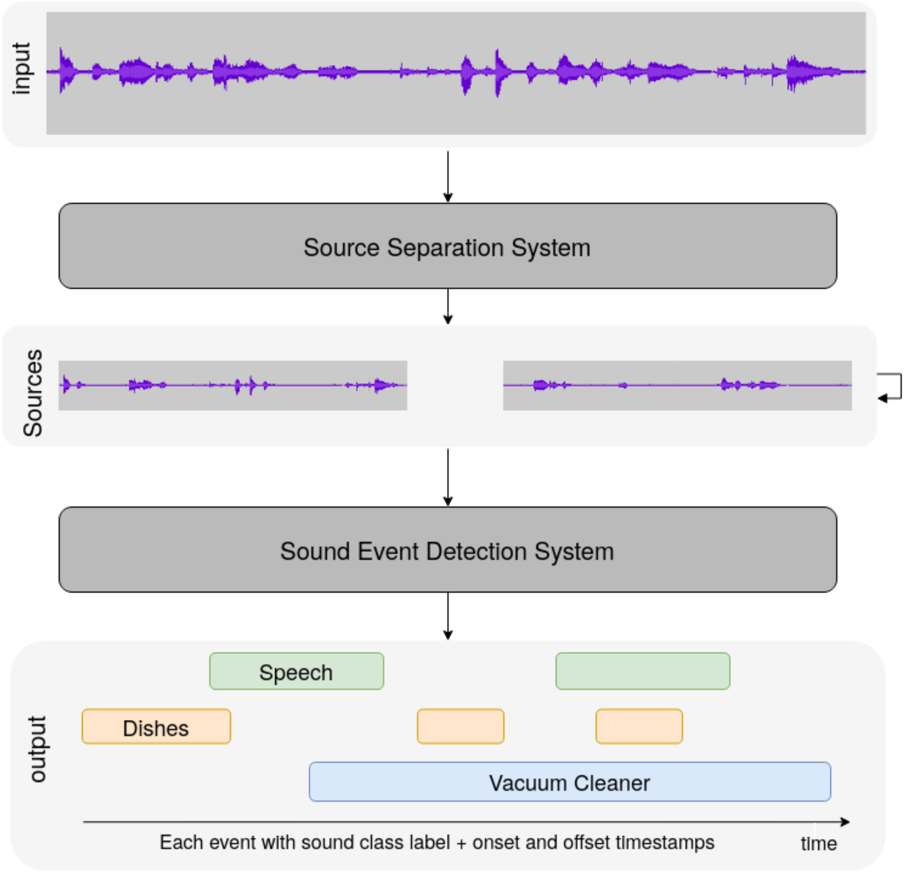
input
Source Separation System
Sources
Sound Event Detection System
output
Speech
Dishes
Vacuum Cleaner
Each event with sound class label + onset and offset timestamps
time

Fig. 16

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Sound Event Detection

Pipeline

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

Sound Event Detection

Pipeline

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

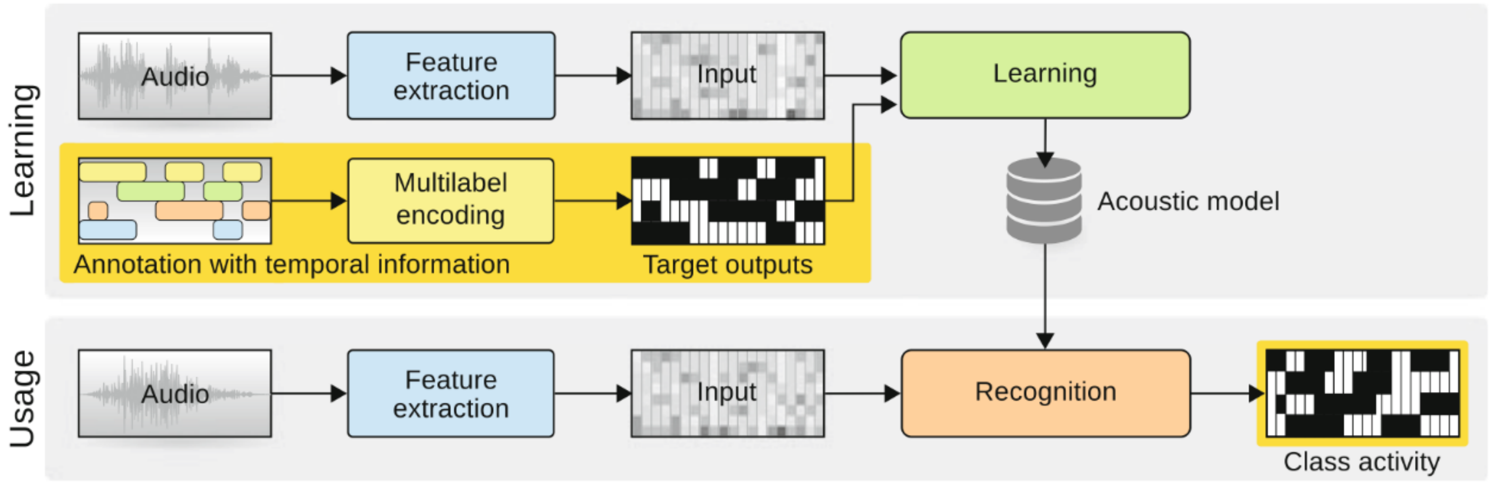

Fig. 8

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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

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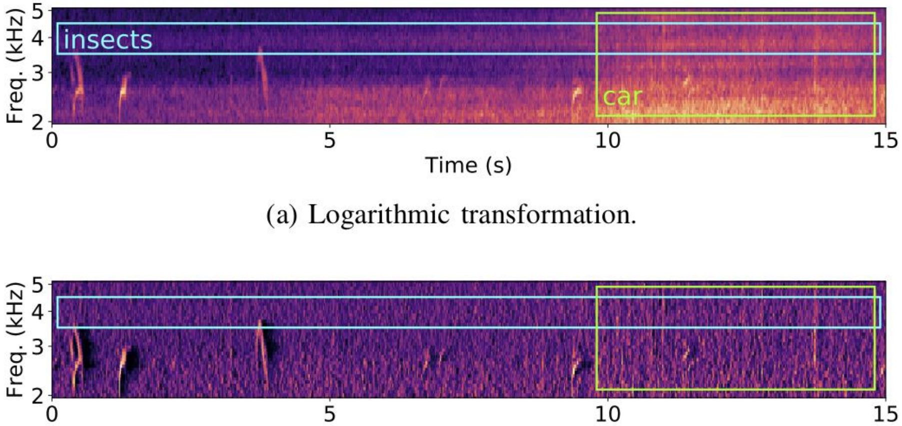
Sound Event Detection
Pipeline

- 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

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Sound Event Detection

Pipeline

- Annotation
    - Quality of “ground truth”? (limited agreement / reliability)

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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

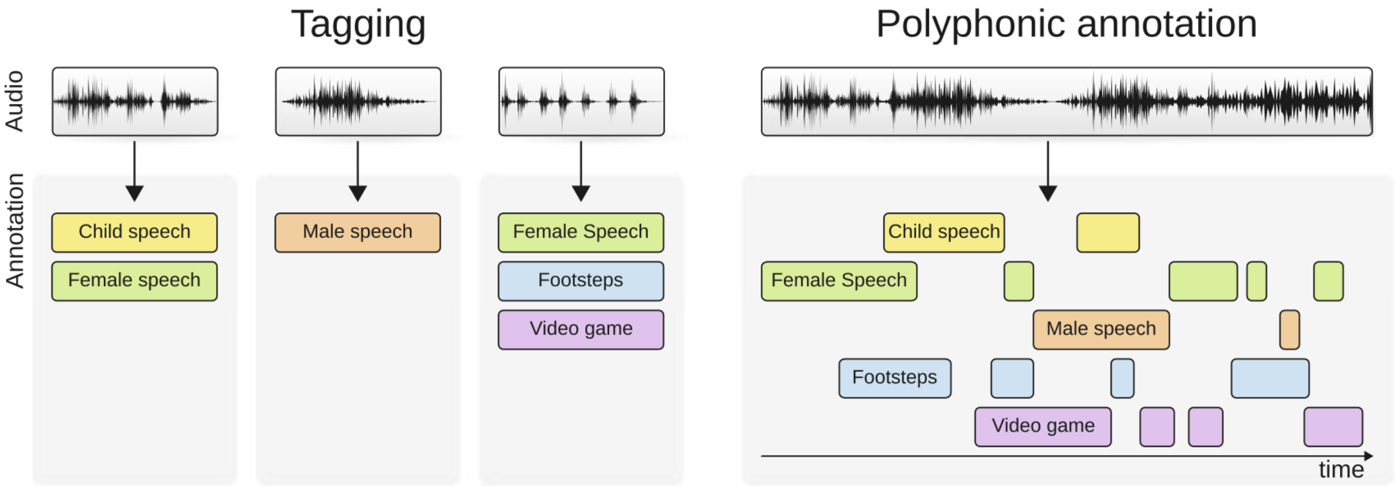

Fig. 10

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Sound Event Detection
Pipeline

- Label encoding
    - Binarized sound activity (0/1)
        - Multilabel classification
        - 1 (independent) binary detector per class

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)

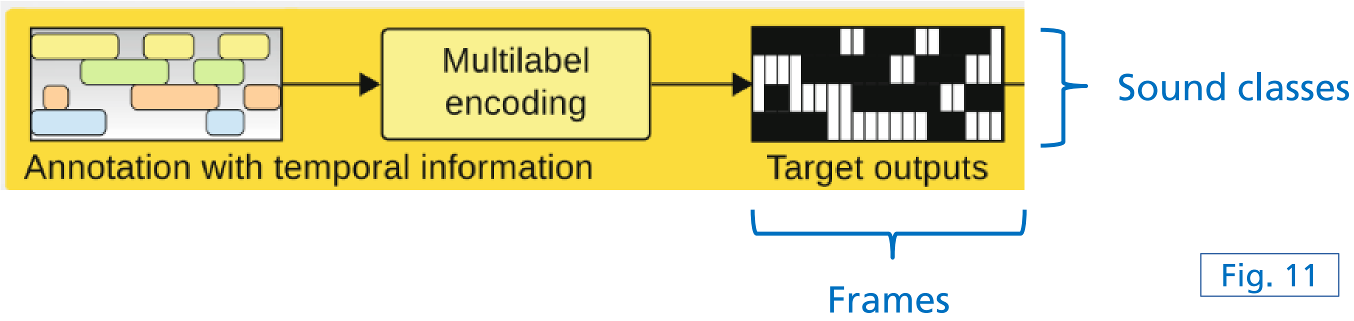

Fig. 11

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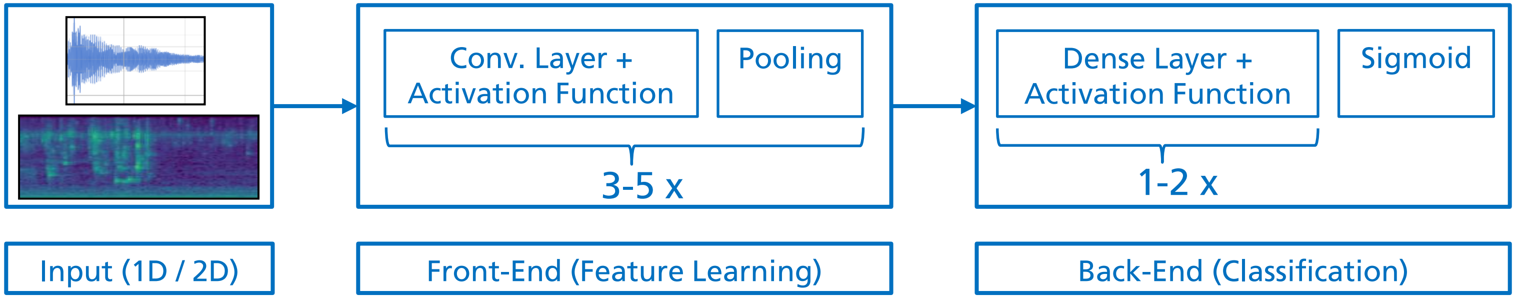
Sound Event Detection

Pipeline

- Typical neural network architectures
    - CNN

Own

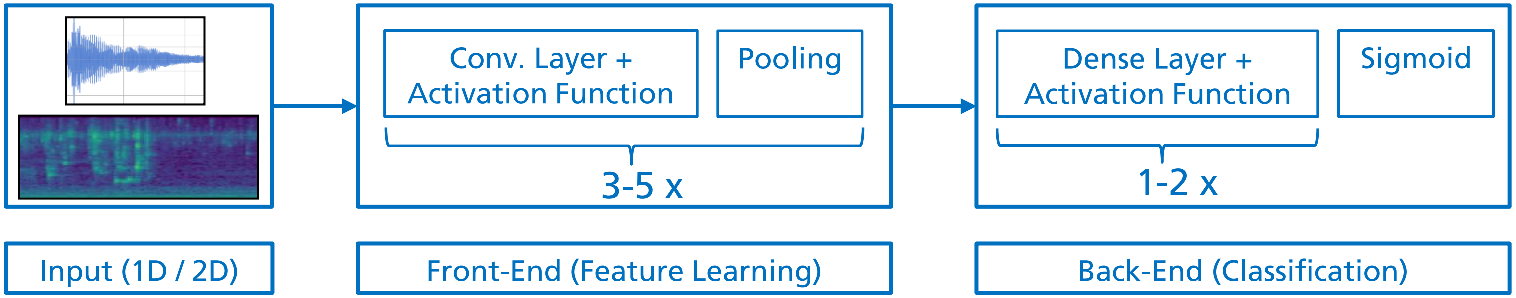

Conv. Layer + Activation Function
Pooling
3-5 x
Dense Layer + Activation Function
Sigmoid
1-2 x
Input (1D / 2D)
Front-End (Feature Learning)
Back-End (Classification)

Sound Event Detection

Pipeline

- Typical neural network architectures
  - CNN

Own



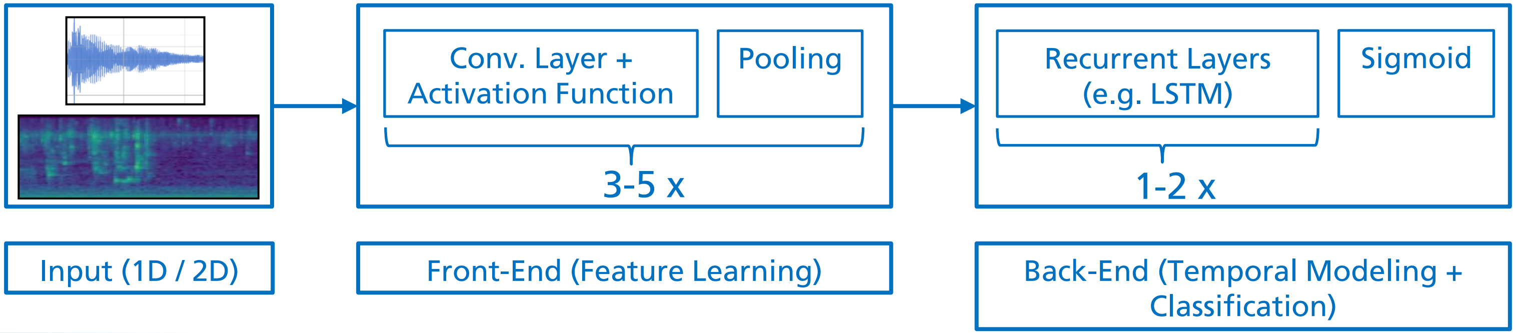
Input (1D / 2D)

Front-End (Feature Learning)

Back-End (Classification)

Conv. Layer + Activation Function
Pooling
3-5 x
Dense Layer + Activation Function
Sigmoid
1-2 x

  - CRNN



Input (1D / 2D)

Front-End (Feature Learning)

Back-End (Temporal Modeling + Classification)

Conv. Layer + Activation Function
Pooling
3-5 x
Recurrent Layers (e.g. LSTM)
Sigmoid
1-2 x

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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

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Sound Event Detection

Pipeline

- Evaluate SED → binary classification results on a frame-level
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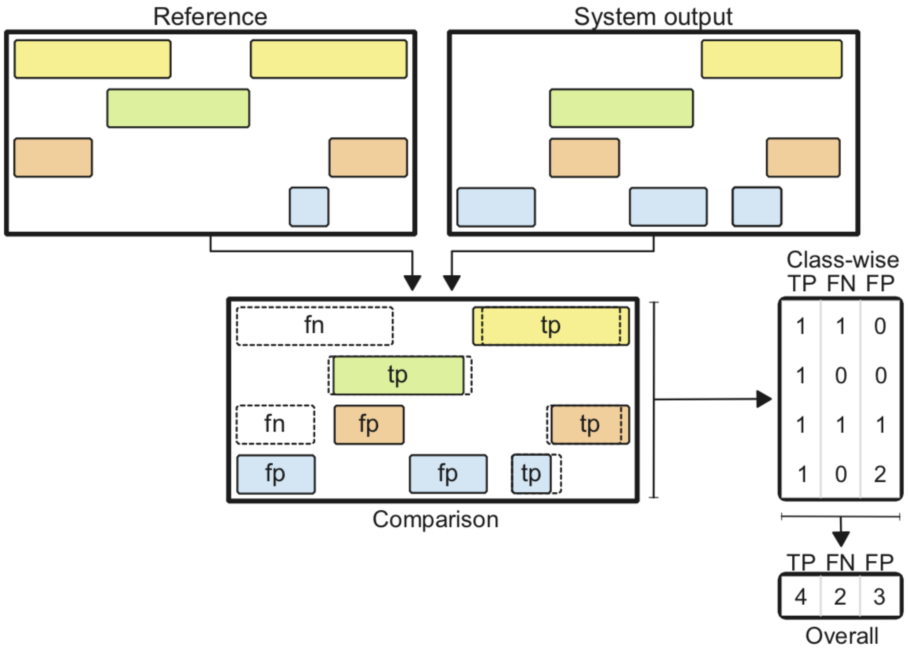

Class-wise

TP	FN	FP
1	1	0
1	0	0
1	1	1
1	0	2

TP	FN	FP
4	2	3

Overall

Fig. 13

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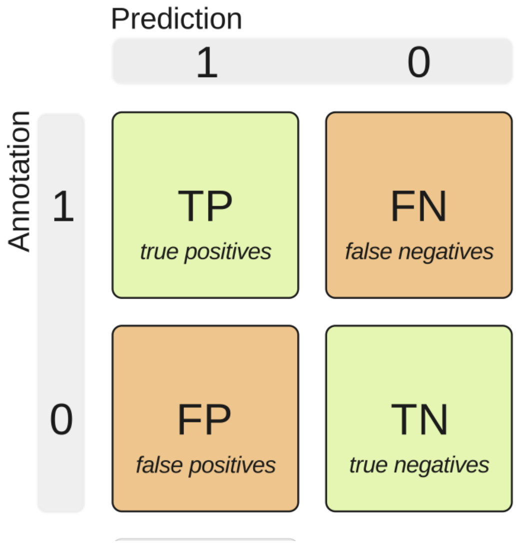
Sound Event Detection

Evaluation Metrics

- Recap: Binary classification evaluation
  - True/false positives (TP/FP)
  - True/false negatives (TN/FN)



		Prediction	
		1	0
Annotation	1	TP *true positives*	FN *false negatives*
	0	FP *false positives*	TN *true negatives*

Fig. 12

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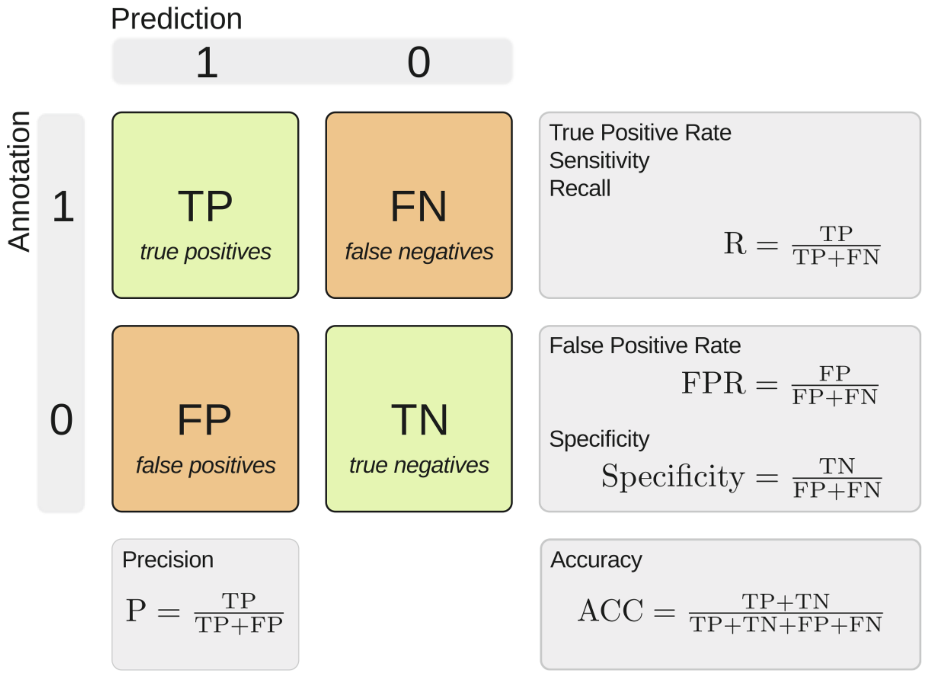
Sound Event Detection

Evaluation Metrics

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



Prediction

1 0

Annotation

1

TP *true positives*

FN *false negatives*

True Positive Rate
Sensitivity
Recall

$$\mathrm{R} = \frac{\mathrm{TP}}{\mathrm{TP+FN}}$$

0

FP *false positives*

TN *true negatives*

False Positive Rate

$$\mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{FP+FN}}$$

Specificity

$$\mathrm{Specificity} = \frac{\mathrm{TN}}{\mathrm{FP+FN}}$$

Precision

$$\mathrm{P} = \frac{\mathrm{TP}}{\mathrm{TP+FP}}$$

Accuracy

$$\mathrm{ACC} = \frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FP+FN}}$$

Fig. 12

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Sound Event Detection

Data Augmentation

- Data Augmentation
  - Increases amount / variability of training data
  - Improves model generalization towards unseen data

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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

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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)

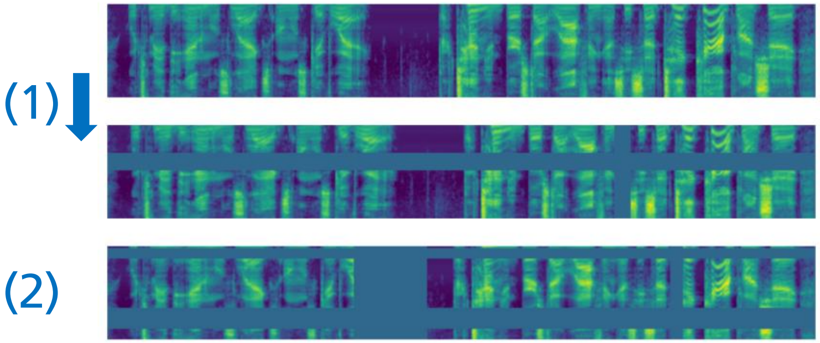

Fig. 19

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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

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

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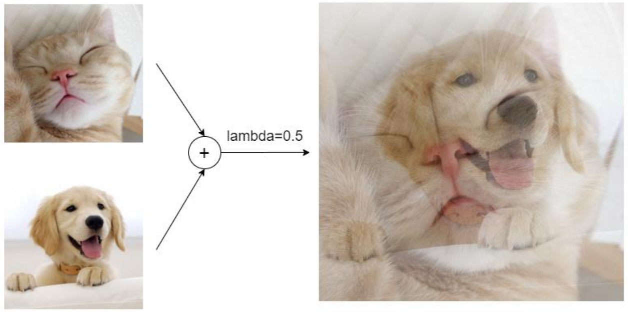
Sound Event Detection

Data Augmentation

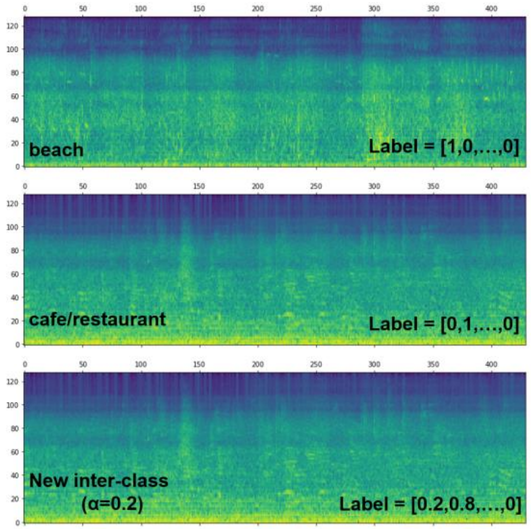
- Methods
  - Mix-up data augmentation [Zhang, 2018]
    - Simulate sound mixtures
    - Mix two data instances with random mixing ratio

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



Computer Vision

Fig. 17



Machine Listening

Fig. 18

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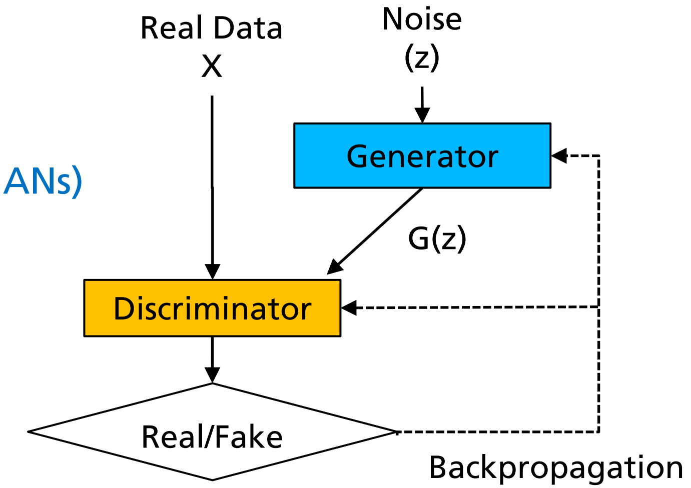
Sound Event Detection
Data Augmentation

- Methods
  - Data Synthesis
    - Example: WaveGAN [Donahue, 2019]
      - Synthesize waveforms with Generative Adversarial Networks (GAN)

Training (GANs)



Own

Fig. 20

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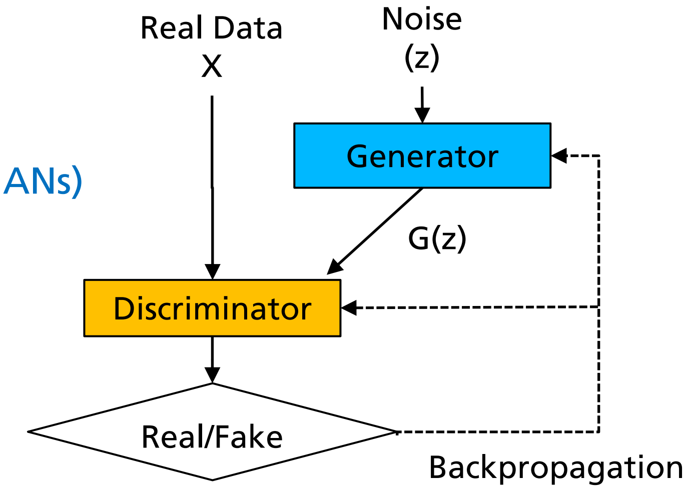
Sound Event Detection
Data Augmentation

- Methods
  - Data Synthesis
    - Example: WaveGAN [Donahue, 2019]
      - Synthesize waveforms with Generative Adversarial Networks (GAN)

Training (GANs)



Own

Synthesis examples (Spectrograms)

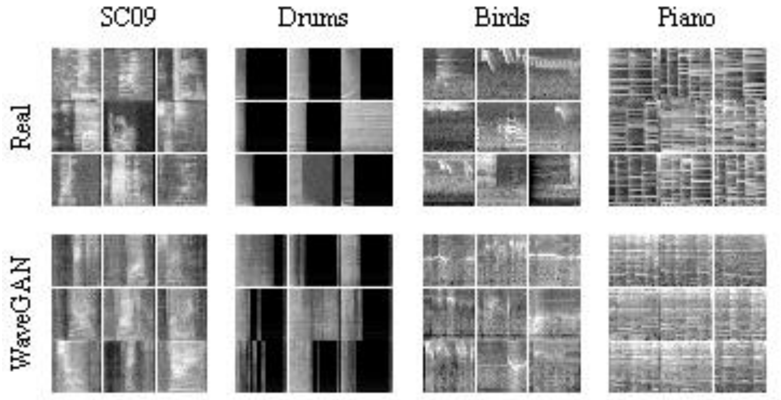


Fig. 20

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Sound Event Detection

Novel Methods

- VGG-style CNN [Sakashita, 2018]
    - Main Idea
        - Pairs of convolutional layers + non-linearity before max pooling
    - Effect
        - Smaller kernel shapes
        - More non-linearities → model is more expressive

Sound Event Detection

Novel Methods

- CRNN [Adavanne, 2017]

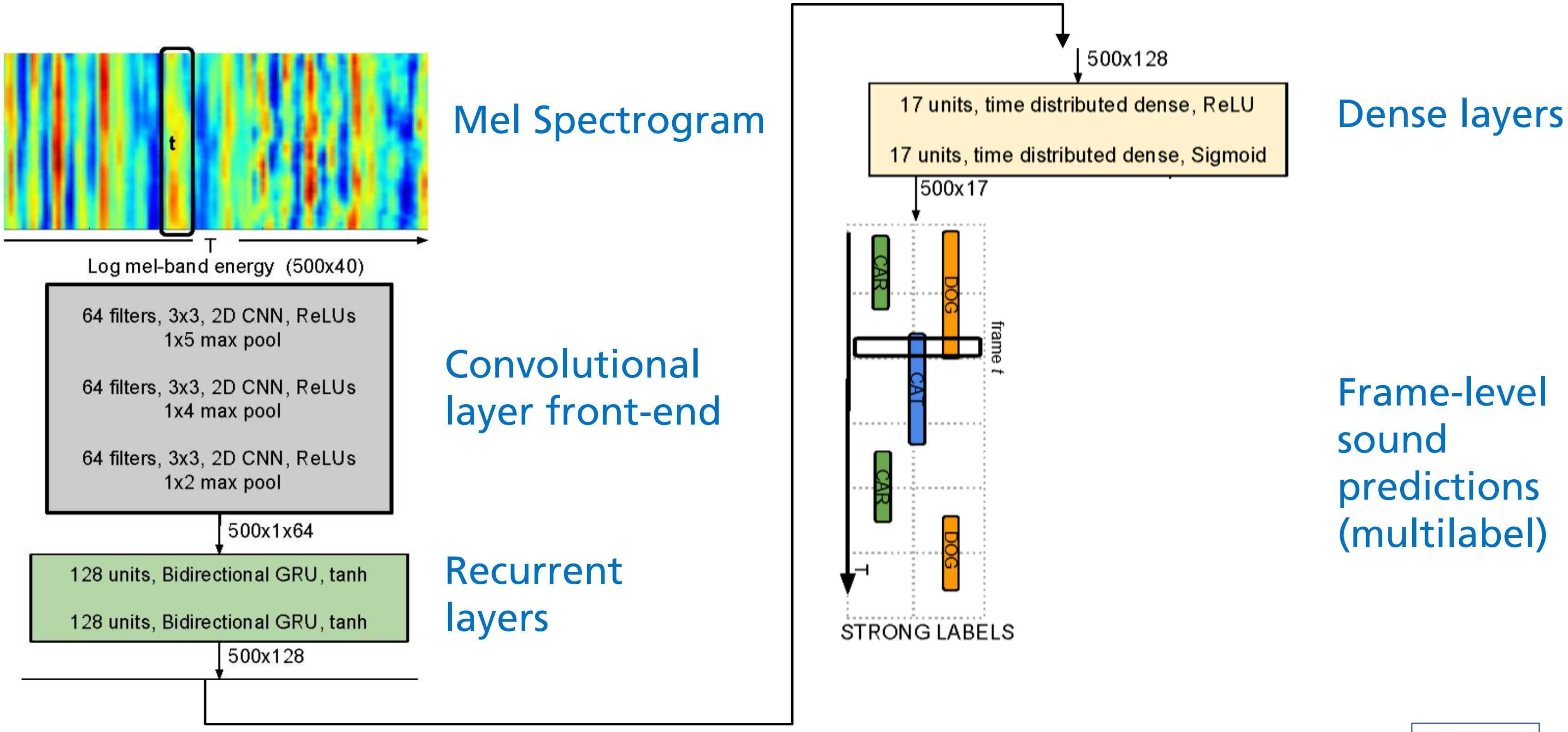
t
T
Log mel-band energy (500x40)
Mel Spectrogram
64 filters, 3x3, 2D CNN, ReLUs
1x5 max pool
64 filters, 3x3, 2D CNN, ReLUs
1x4 max pool
64 filters, 3x3, 2D CNN, ReLUs
1x2 max pool
Convolutional layer front-end
500x1x64
128 units, Bidirectional GRU, tanh
128 units, Bidirectional GRU, tanh
Recurrent layers
500x128
500x128
17 units, time distributed dense, ReLU
17 units, time distributed dense, Sigmoid
Dense layers
500x17
CAR
DOG
CAT
CAR
DOG
frame t
T
STRONG LABELS
Frame-level sound predictions (multilabel)

Fig. 23

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Sound Event Detection

Novel Methods

- CRNN + Attention [Xu, Kong, et al., 2018]
    - Add parallel convolutional layers to act as gate to feature maps

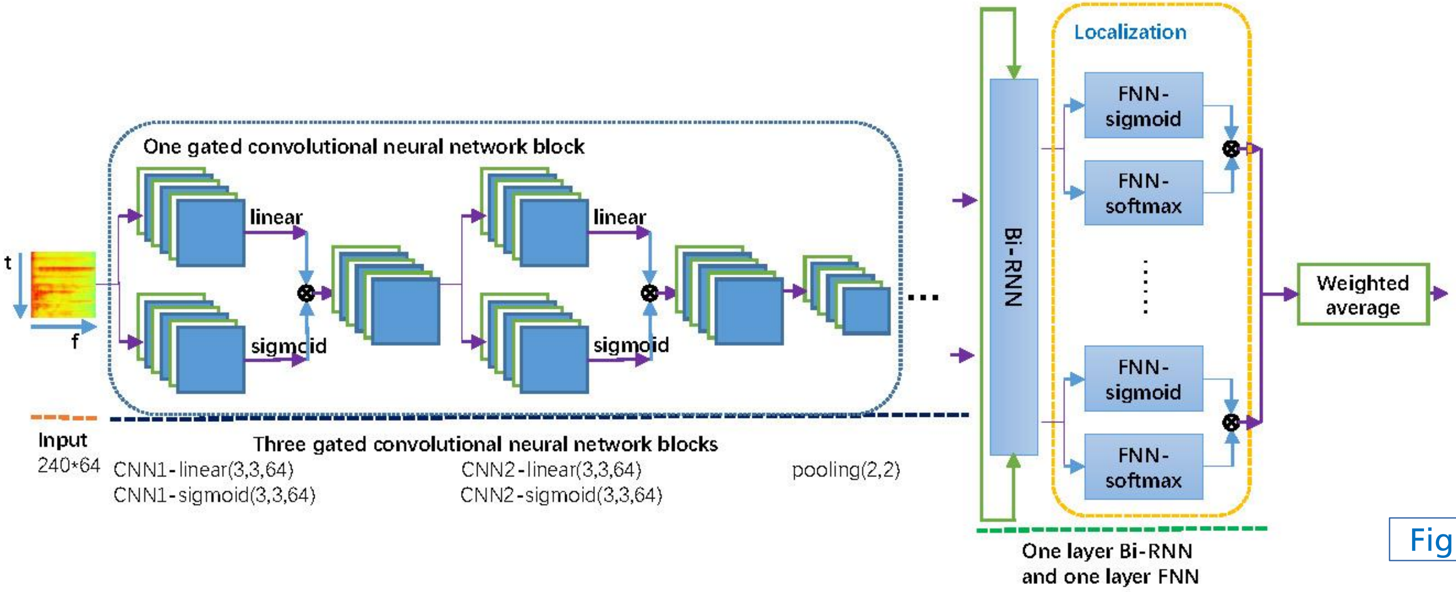

Fig. 24

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Sound Event Detection

Novel Methods

- CRNN + Attention [Xu, Kong, et al., 2018]
  - Add parallel convolutional layers to act as gate to feature maps
  - Attention allows network to better focus on relevant regions
  - Similar approach for better event localization after RNN layer

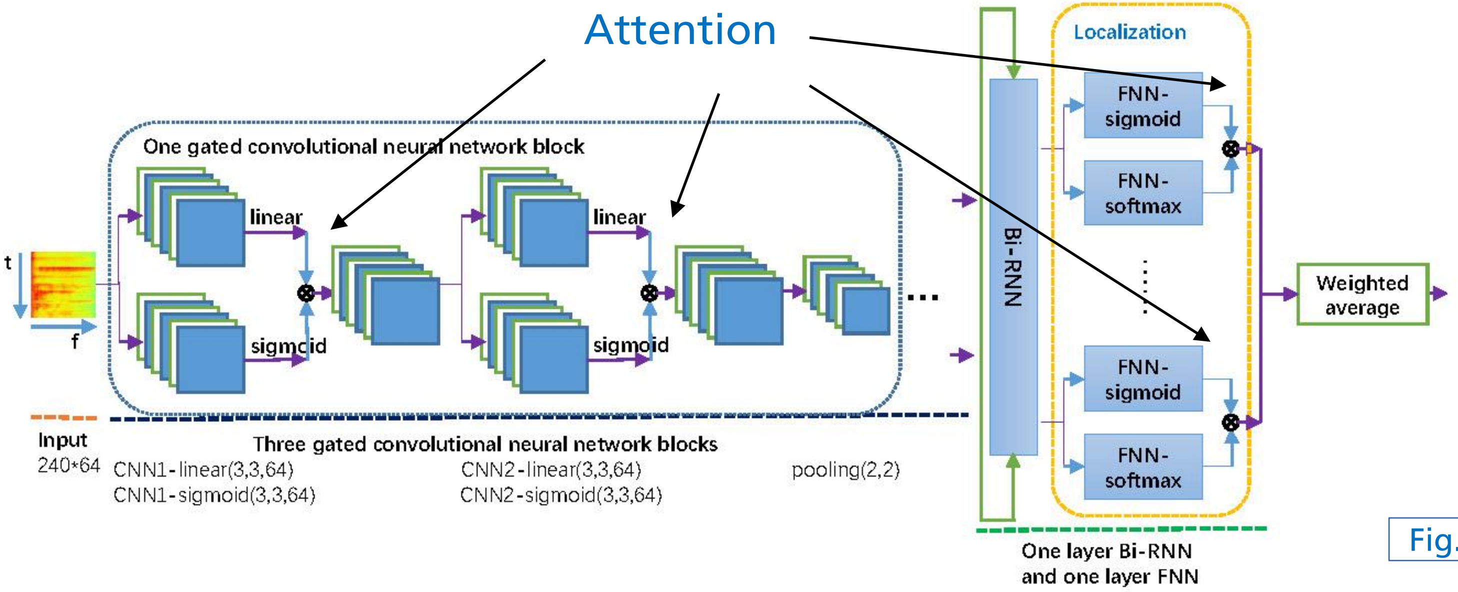

Fig. 24

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Summary

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

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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

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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. 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

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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

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Thank you!

- Any questions?

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