Recurrent neural networks for polyphonic sound event detection in real life recordings

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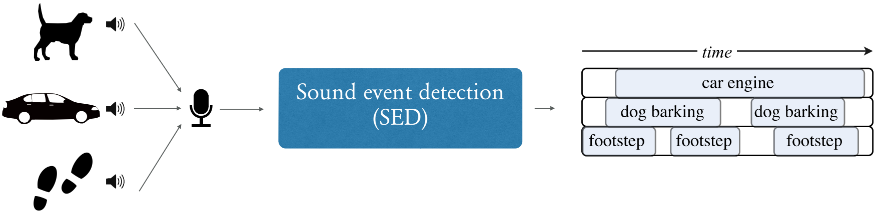
Overview

1. Introduction
2. Method
3. Evaluation

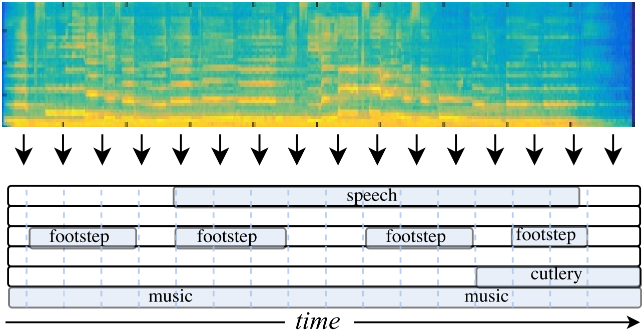
Polyphonic sound event detection in real life recordings

Goal: detect **which** sources are active, **beginning** and **ending** moments.



Polyphonic sound event detection

- A multilabel classification task.
- Map input signal to class labels in short time windows (~50ms)



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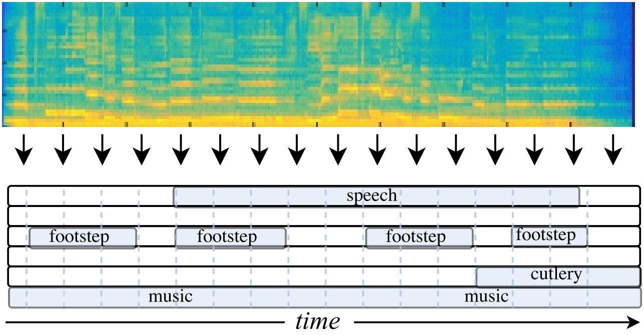

Previous work

Context dependent

- GMM+HMM
- Nonnegative matrix factorisation (NMF)

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- Deep feedforward neural networks (FNN)

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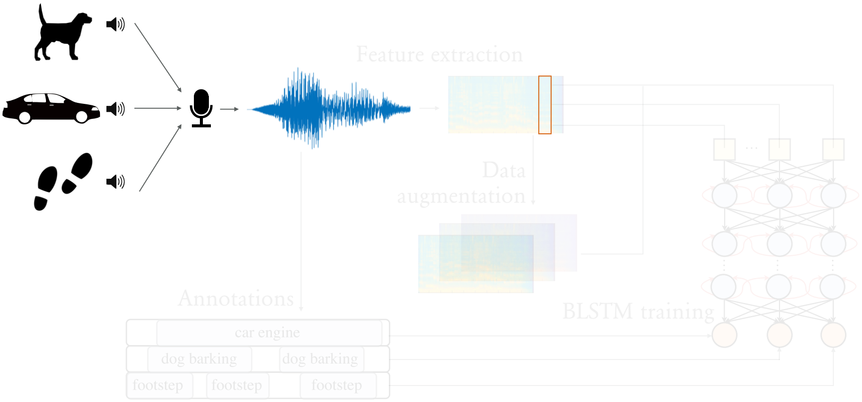

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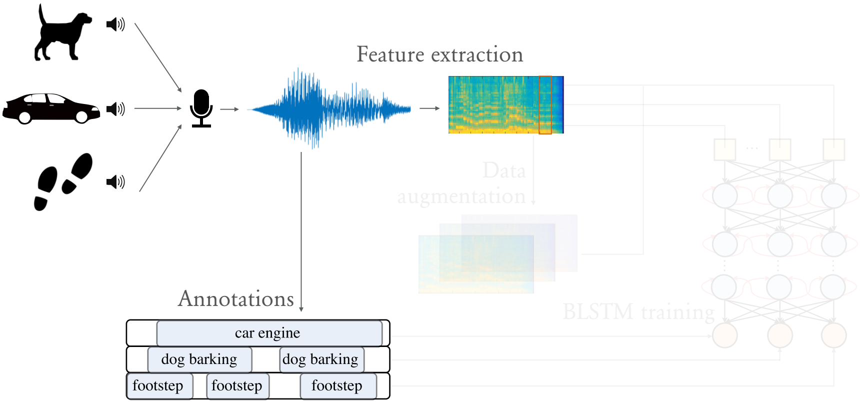

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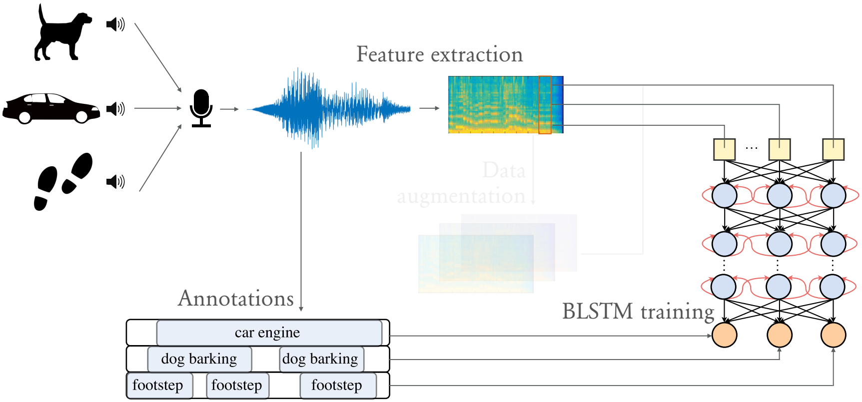

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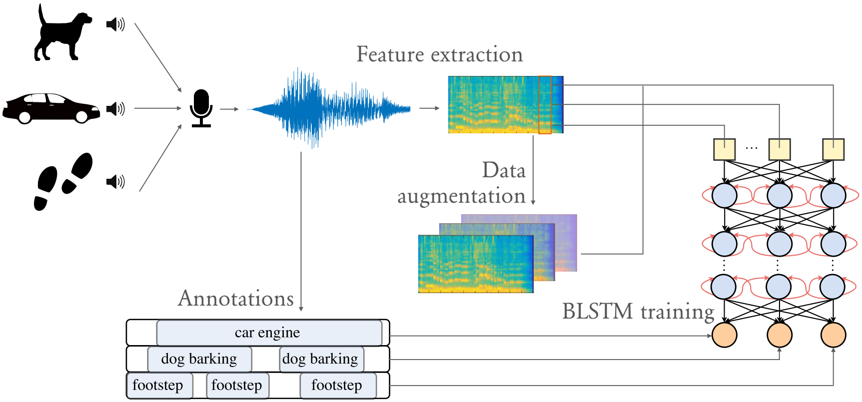
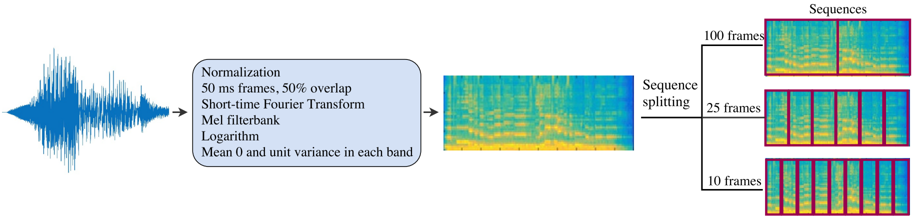


Feature extraction



Log mel energies, ZMUV, split in sequences at three different timescales (10, 25, 100 frames).

The data needs to be annotated: each class is marked as *active* (1) or *inactive* (0) in each frame.

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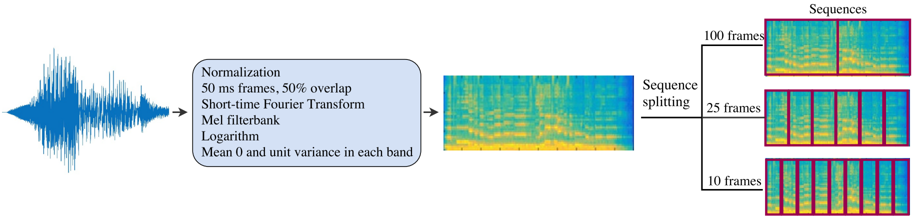

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Recurrent neural network (RNN)

For an input sequence $\{\mathbf{x}_1, \ldots, \mathbf{x}_T\}$, compute a sequence of hidden activations $\{\mathbf{h}_1, \ldots, \mathbf{h}_T\}$ and output vectors $\{\hat{\mathbf{y}}_1, \ldots, \hat{\mathbf{y}}_T\}$ as

$$\mathbf{h}_t = \mathcal{F}(\mathbf{W}^{\mathrm{xh}}\mathbf{x}_t + \mathbf{W}^{\mathrm{hh}}\mathbf{h}_{t-1} + \mathbf{b}^{\mathrm{h}}) \tag{1}$$

$$\hat{\mathbf{y}}_t = \mathcal{G}(\mathbf{W}^{\mathrm{h}\hat{\mathrm{y}}}\mathbf{h}_t + \mathbf{b}^{\hat{\mathrm{y}}}) \tag{2}$$

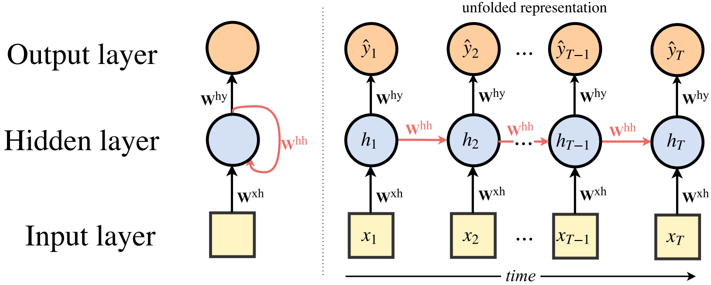


Figure: On the left, a recurrent neural network with 1 hidden layer and a single neuron. On the right, the same network unfolded in time over T steps.

Bidirectional RNN (BRNN) [1]

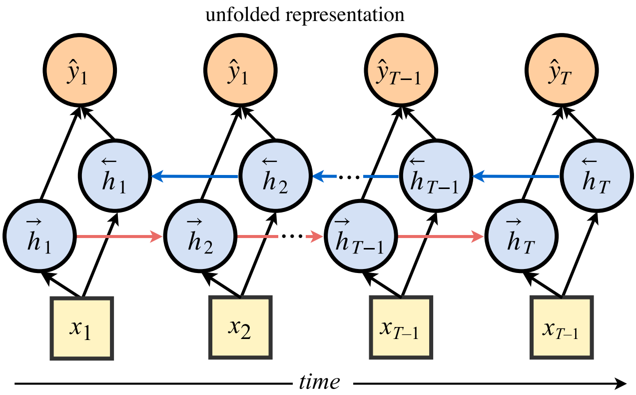
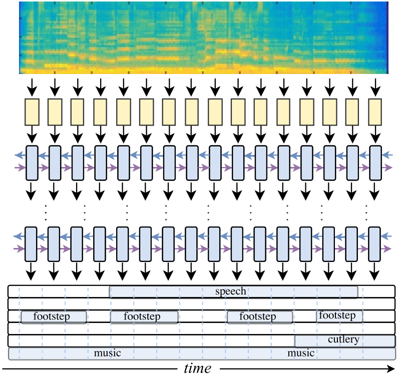


Figure: A bidirectional recurrent neural network with one hidden layer and two hidden neurons unfolded in time.

[1] Schuster et al., IEEE Trans. on Sgn. Processing (1997)

Model

- Bidirectional RNN with LSTM units (BLSTM)
- Multiple stacked recurrent hidden layers
- One output vector for each frame ("sequence to sequence")
- Output layer with sigmoids predicts posterior probabilities for each class of being active. Multilabel $\Longrightarrow$ no softmax
- At test time threshold predictions for binary activities



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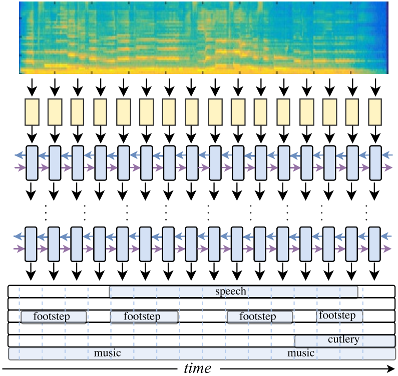

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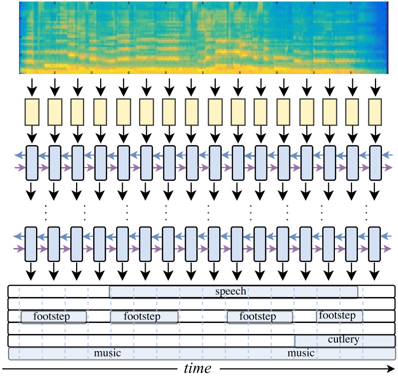

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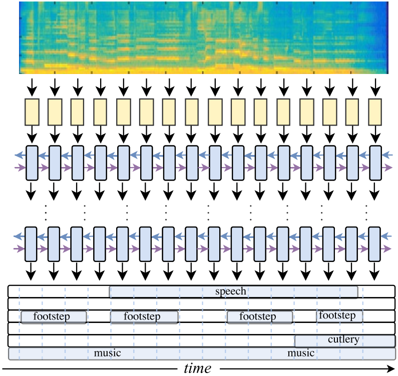

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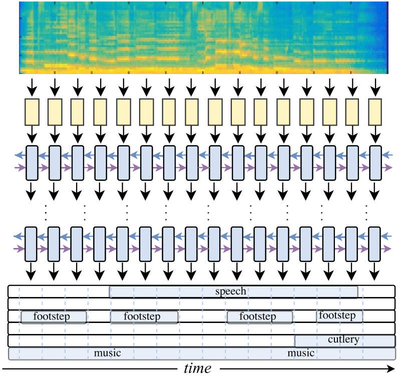
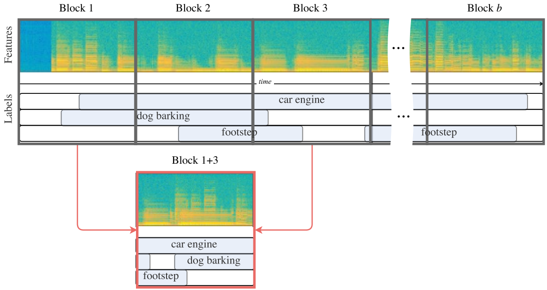


Data augmentation

Three techniques:

- Block mixing
- Time stretching
- Sub-frame time shifting

All performed directly in the time-frequency domain, on the extracted features.



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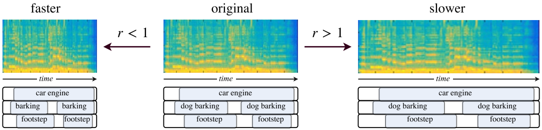

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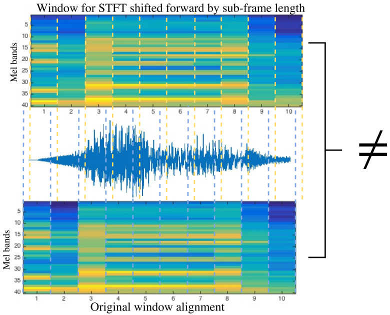

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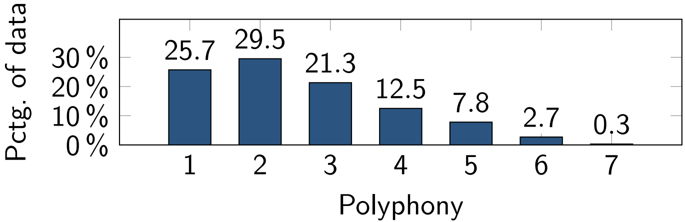
Dataset

CASA 61 classes from 10 contexts, real life recordings.
18 hours. 5 folds of training, validation and test.
Average polyphony 2.53



Augmentations:

- $\times$16 all combined (in the tables **+DA**)
  - Block mixing: 20 blocks per context, mixing 2 at the time $\times$9.5
  - Time stretching: stretching coeff {0.7, 0.85, 1.2, 1.5} $\times$4.25
  - Sub-frame time shifting: three times $\times$3

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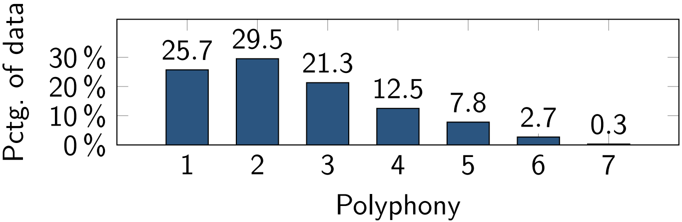

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Metrics

Overall metric is the average of the scores in each of the 10 contexts.

1. Framewise F1
2. 1-second F1

Neural nets used in the experiment

- 40 input neurons, each reading one band of the log mel energies
- 4 recurrent (BLSTM) hidden layers
- 200 LSTM blocks in each (100 forwards, 100 backwards)
- 850K parameters in total
- Optimizer: RMSprop
- Objective function: RMSE (cross entropy didn't work as well)
- Package: Currennt (CUDA/C++)
- 5 nets trained from random init for each fold, then pick the best on validation.
- At test time 100-frames sequences, threshold at 0.5
- Also tests using only LSTM (no bidirectional)
- No smoothing step required, RNN takes care of temporal continuity

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Results

Comparing to the approach in [Cakir et al., 2015], which uses a FNN (MLP with maxout) with 1.6M parameters (double those of the RNN), where the outputs are smoothed using a median filter.

Table: Overall $F1$ scores, as average of individual contexts scores, for the FNN, the proposed LSTM and BLSTM, and BLSTM with data augmentation (+DA).

Method	$F1_{\text{AvgFram}}$	$F1_{\text{1-sec}}$
FNN [Cakir et al., 2015]	58.4%	63.0%
LSTM	62.5%	63.8%
BLSTM	64.0%	64.6%
BLSTM+DA	**64.7%**	**65.5%**

BLSTM+DA improves the performance over the FNN by relative 15.1% and 6.8% for $F1_{\text{AvgFram}}$ and $F1_{\text{1-sec}}$ respectively.

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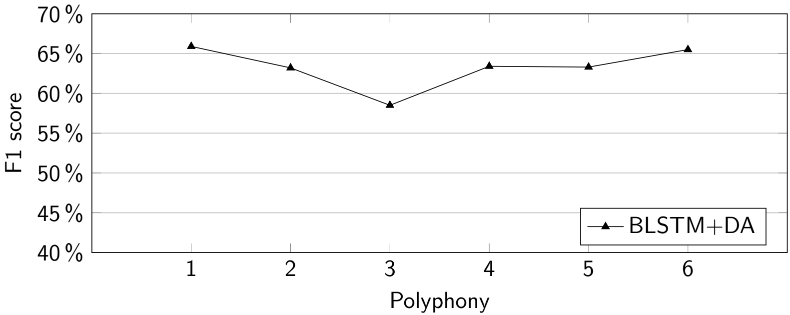
Results — individual contexts

	$F1_{\text{AvgFram}}$		
	FNN	**BLSTM**	**BLSTM+DA**
basketball	70.2%	77.4%	**78.5%**
beach	**49.7%**	46.6%	49.6%
bus	43.8%	45.1%	**49.4%**
car	53.2%	67.9%	**71.8%**
hallway	47.8%	**58.1%**	54.8%
office	77.4%	**79.9%**	74.4%
restaurant	69.8%	76.5%	**77.8%**
shop	51.5%	**61.2%**	61.1%
street	62.6%	**65.3%**	65.2%
stadium	58.2%	61.7%	**64.3%**
average	58.4%	64.0%	**64.7%**

Results — polyphony

Quite robust to polyphony increase



Demo

Demo time!

Discussion

1. RNNs improve over FNNs in polyphonic SED, and with half the parameters.
2. Overfitting, the main issue encountered $\implies$ much more data needed
3. Data augmentation helps slightly reducing overfitting.
4. Quite robust to high polyphony.

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The End

— Q&A —