

# Convolutional neural networks can learn duration for detecting pitch accents and lexical stress

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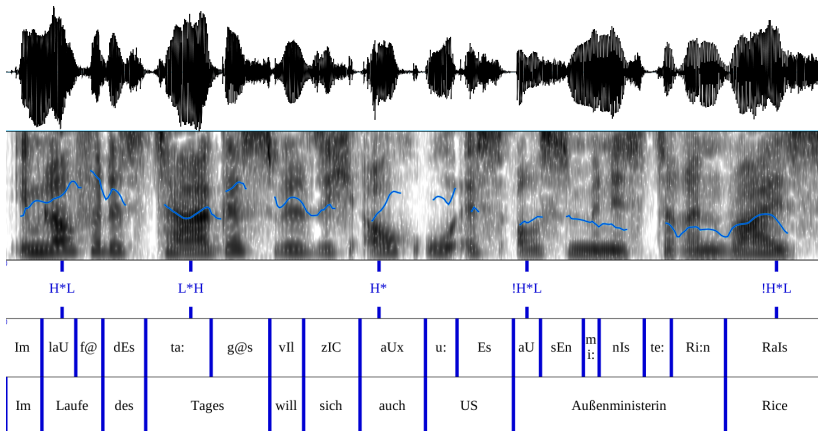


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**Maschinelle  
Sprachverarbeitung**

# Introduction

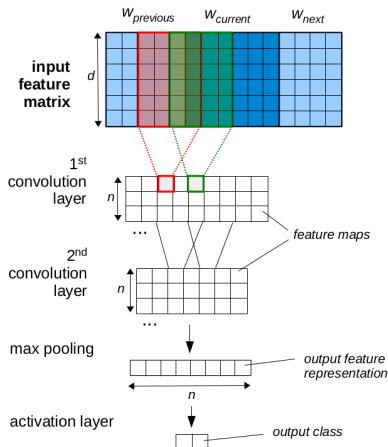
- ▶ **pitch accent detection**  
detect which words or syllables are pitch accented
- ▶ **lexical stress detection**  
detect which syllables carry (primary) lexical stress
- ▶ input: force-aligned speech data (or ASR output)
- ▶ similar acoustic features
- ▶ **duration** is an important correlate

# DIRNDL example



# Pitch accent detection with convolutional neural networks

- ▶ **advantage:** requires very little preprocessing
- ▶ CNN learns high-level feature representation
- ▶ input: 3-word input window
- ▶ frame-based acoustic features
  - ▶ f0, energy, loudness, voicing probability, HtNR, zero-crossing rate
- ▶ 2 convolution layers



Stehwien & Vu (2017), Prosodic event recognition using convolutional neural networks with context information. *Proceedings of Interspeech*

## Contributions

**duration** is not an explicit input feature, but provided implicitly by the number of frames for each input word

Experiments test the following **assumptions**:

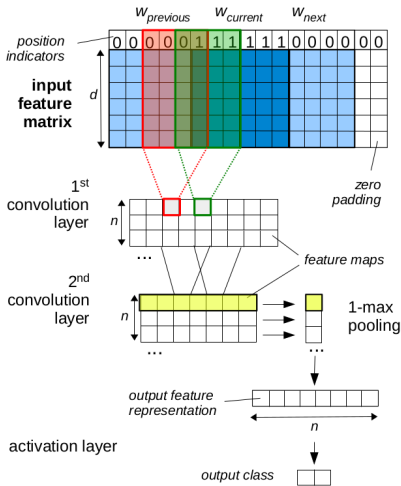
1. the CNN can learn this information on its own
2. method of pooling and padding affects how duration is captured

Tested on several **tasks**:

- ▶ pitch accent detection and classification
- ▶ word- and syllable-level
- ▶ lexical stress detection
- ▶ **Data**: DIRNDL German radio news corpus

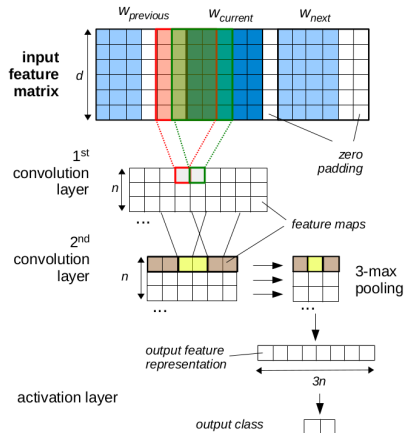
# 1-max pooling with position indicators

- ▶ max pooling selects single neuron with highest activation in each feature map
- ▶ zero padding at end of word
- ▶ position indicator features mark frames of current word
- ▶ kernels span all features
- ▶ 100 feature maps
- ▶ output feature vector:  $n = 100$



## 3-max pooling

- ▶ zero padding at end of each word
- ▶ 3 max pooling windows of equal size
- ▶ 30 feature maps
- ▶ output feature vector:  $3n = 90$



## Comparison of pooling methods

Compared 1-max to 3-max pooling on word-based pitch accent detection

### Results:

- ▶ 1-max pooling
  - ▶ requires position indicators
  - ▶ padding in between words: slight improvement
- ▶ 3-max pooling does not require position indicators

setting		+ pos.-ind. (F1)	- pos.-ind. (F1)
<i>1-max pooling</i>	padding at end	<b>86.8</b>	63.4
	padding between words	86.2	70.4
<i>3-max pooling</i>	padding between words	85.8	<b>86.0</b>



# Evidence of duration in CNN output representations

**Assumptions:** (1) CNN learns duration on its own,  
(2) pooling and padding have different effects

## Method:

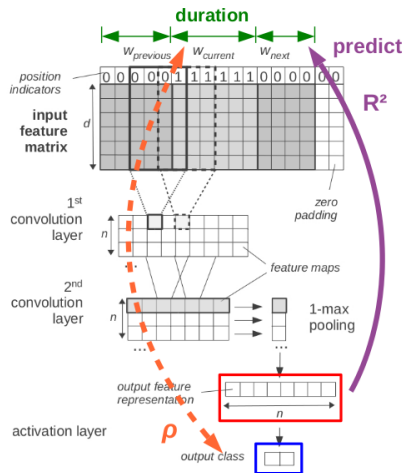
- ▶ use CNN output representation to predict duration
- ▶ if duration can be approximated  $\Rightarrow$  encoded in CNN features
- ▶ the better the fit, the more duration information has been learned
- ▶ expected to depend on the task  
→ the more important duration is, the better it should be predicted

## Recognition tasks

1. word-based pitch accent detection
2. syllable-based pitch accent detection
3. lexical stress detection (syllables)
4. pitch accent detection on stressed syllables only
5. pitch accent classification (syllables)  
*not considering the "none" class!*
  - ▶ H\* vs. H\*L vs. L\*H
  - ▶ H\*L vs. L\*H

## Linear model analysis

- ▶ train linear regression model on CNN output
- ▶ predict duration of each input word/syllable
- ▶ goodness of fit  $R^2 \Rightarrow$  estimation of encoded information
- ▶ compare correlation between duration and target label (Spearman's  $\rho$ )



## Results: Duration in CNN output representations

task/setting		1-max pooling			3-max pooling		
measure	$\rho$	$R^2$			$R^2$		
duration	$W_{cur}$	$W_{prev}$	$W_{cur}$	$W_{next}$	$W_{prev}$	$W_{cur}$	$W_{next}$
<i>word-based</i>							
PA detection	0.70	0.11	0.64	0.09	0.48	0.61	0.41
- pos.-ind.		0.06	0.14	0.06			
<i>syllable-based</i>							
PA detection	0.34	0.06	0.42	0.06	0.16	0.40	0.18
stress detection	0.22	0.11	0.31	0.07	0.31	0.38	0.32
PA detection str.-only	0.36	0.09	0.40	0.06	0.24	0.38	0.21
H*/H*L/L*H	-0.04	0.05	0.16	0.12	0.21	0.19	0.15
H*L/L*H	-0.04	0.03	0.14	0.07	0.09	0.17	0.08

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duration of current word can be approximated  
 $\Rightarrow$  encoded in CNN output representation

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correlation between target label and duration explains fit

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1-max pooling: context word durations not learned well

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3-max pooling: more context information captured, but current word most important



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duration more important for pitch accent detection on words than on syllables → correlation with word length

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no correlation with pitch accent type if presence is given →  
duration more important for detection than type distinction

## Summary

- ▶ analysis based on linear models provides evidence that certain information is encoded in the CNN output
- ▶ **conclusion:** CNN-based pitch accent detector can learn duration on its own from frame-based input
- ▶ considered syllable-based tasks and lexical stress detection: correlation with target label matters
- ▶ compared 1-max pooling to 3-max pooling  
→ in both cases, the duration of the current word/syllable is learned best

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