# Automatic classification of lexical stress errors for German CAPT

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## Lexical stress: Accentuation/prominence of syllable(s) in a word

## In German:

- Variable placement, contrastive function um·FAHR·en vs. UM·fahr·en to drive around to run over
- Reflected by duration, F0, intensity
- Impacts intelligibility of non-native (L2) speech



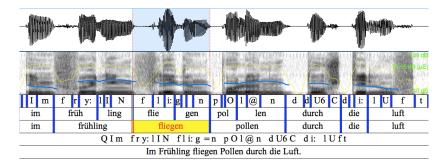
- ► Contrastive lexical stress (LS) difficult for French speakers
- CAPT can help; requires automatic diagnosis
- Classification of LS errors in L2 German unexplored

## Classification of LS errors by French learners of German How feasible is it? Which features are most useful?





# Subset of IFCASL corpus of French-German speech (Fauth et al. 2014)



Extracted utterances of 12 bisyllabic, initial-stress words

- ▶ 668 tokens from 56 French speakers manually annotated
- ▶ 477 tokens from 40 German speakers assumed correct



- Each token assigned a class label: [correct], [incorrect], [none] [bad\_nsylls], [bad\_audio]
- ► 15 annotators (12 native), each token labeled by ≥2
- Varying phonetics/phonology expertise

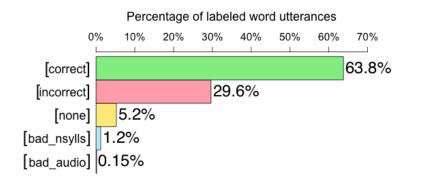


#### Overall pairwise inter-annotator agreement

|                  | Mean   | Maximum | Median | Minimum |
|------------------|--------|---------|--------|---------|
| % Agreement      | 54.92% | 83.93%  | 55.36% | 23.21%  |
| Cohen's $\kappa$ | 0.23   | 0.61    | 0.26   | -0.01   |

- Variability not explained by annotator L1 or expertise
- Single gold-standard label selected for each token







Train & evaluate CART classifiers using WEKA toolkit

#### Training data

- Manually annotated L2 utterances
- Automatically annotated L1 utterances (all [correct])

## Held-out testing data

- ► Feature comparison: 1/10 of L2 utterances (random)
- ► Unseen speakers: all utterances from 1 of 56 L2 speakers

## Evaluation

- Compute agreement (% and κ) with gold standard
- Cross-validation (10 or 56 folds)



#### Prosodic feature sets

- DUR Duration (relative syllable & nucleus lengths)
- ► F0 Fundamental frequency (mean, max., min., range)
- INT Intensity (mean, max.)

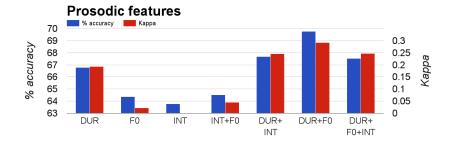
Pitch and energy contours calculated using JSnoori software (http://jsnoori.loria.fr)



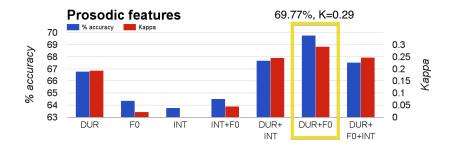
#### Other features

- ► WD Word uttered (e.g. *Flagge*)
- ► LV Speaker's CEFR skill level (A2|B1|B2|C1)
- AG Speaker's age/gender (Girl|Boy|Woman|Man)

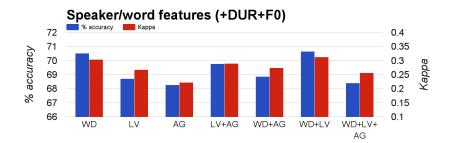




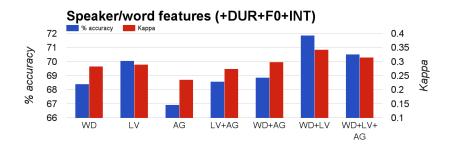






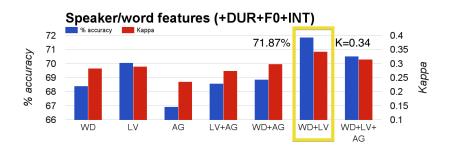




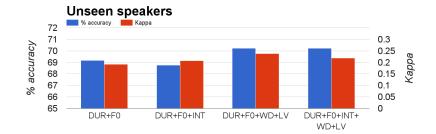


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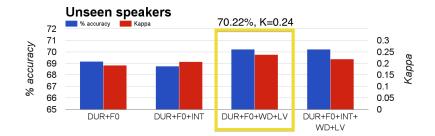














|   | % agreement      | $\kappa$     |
|---|------------------|--------------|
| Best classifier vs. gold standard                           |                  |              |
| Random test set   | 71.87%           | 0.34         |
| Unseen speakers   | 70.22%           | 0.24         |
| Majority ([correct]) classifier vs. gold<br>Human vs. human | 63.77%<br>54.92% | 0.00<br>0.23 |

- Results are encouraging in this context
- Still want better performance for real-world use



- Classification-based diagnosis of lexical stress errors novel approach in German CAPT
- Results of >70% accuracy encouraging (especially considering low human-human agreement)
- Still much room for improvement

#### Future directions

- More powerful machine learning algorithms
- Additional features (e.g. vowel quality, phrase information)
- Online, semi-supervised learning/active learning