# Automatic diagnosis and feedback for lexical stress errors in non-native speech: Towards a CAPT system for French learners of German

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#### Lexical stress



Some syllable(s) in a word more accentuated/prominent<sup>1</sup>

um·FAHR·en vs. UM·fahr·en to run over to drive around

- German: variable stress placement, contrastive stress<sup>1</sup>
- ► French: no word-level stress, final syllable lengthening<sup>2</sup>

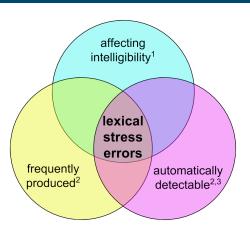
Goal: Computer-Assisted Pronunciation Training (CAPT) for lexical stress errors for French learners of German

<sup>&</sup>lt;sup>1</sup>A. Cutler. "Lexical Stress". In: *The Handbook of Speech Perception*. Ed. by D. B. Pisoni and R. E. Remez. 2005, pp. 264–289.

<sup>&</sup>lt;sup>2</sup>M.-C. Michaux and J. Caspers. "The production of Dutch word stress by Francophone learners". In: *Proc. of the Prosody-Discourse Interface Conference (IDP)*. 2013, pp. 89–94.

#### Lexical stress errors in CAPT





<sup>&</sup>lt;sup>1</sup>U. Hirschfeld. *Untersuchungen zur phonetischen Verständlichkeit Deutschlernender.* Vol. 57. Forum Phoneticum. 1994

<sup>&</sup>lt;sup>2</sup>A. Bonneau and V. Colotte. "Automatic Feedback for L2 Prosody Learning". In: *Speech and Language Technologies*. Ed. by I. lpsic. InTech, 2011

<sup>&</sup>lt;sup>3</sup>Y.-J. Kim and M. C. Beutnagel. "Automatic assessment of American English lexical stress using machine learning algorithms". In: *SLaTE*. 2011, pp. 93–96

#### Outline



#### Lexical stress errors by French learners of German

Annotation of a learner speech corpus Inter-annotator agreement Frequency & distribution of errors

#### Diagnosis methods

Word prosody analysis
Diagnosis by comparison
Diagnosis by classification

#### Feedback methods

de-stress: A prototype CAPT tool

Conclusion

## Lexical stress errors in learner speech



- How reliably can human annotators identify errors in learner utterances?
- How frequently are errors actually produced by French learners of German?



#### Data: IFCASL corpus of French-German speech<sup>1</sup>

- German utterances by French and German speakers
  - Adults (>18) and children (15-16)
  - Levels A2, B1, B2, C1 (children all A2/B1)
- Word- and phone-level segmentations (syllable level added automatically)
- Selected 12 word types (bisyllabic, initial stress)

#### Dataset for annotation:

668 German word utterances by ∼55 French speakers

<sup>&</sup>lt;sup>1</sup>C. Fauth et al. "Designing a Bilingual Speech Corpus for French and German Language Learners: a Two-Step Process". In: *9th Language Resources and Evaluation Conference (LREC)*. Reykjavik, Iceland, 2014, pp. 1477–1482.



#### 15 Annotators, varying by:

- ► Native language (L1):
  - 12 German
  - 2 English (US)
  - 1 Hebrew
- Phonetics/phonology expertise:
  - 2 Experts
  - 10 Intermediates
  - 3 Novices



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#### Praat annotation tool:



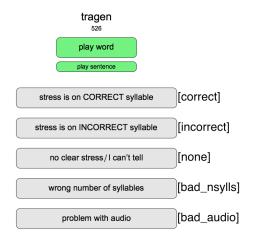


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#### Praat annotation tool:



## Inter-annotator agreement



How reliably can human annotators identify errors in learner utterances?

- Agreement calculated for each pair of annotators who labeled the same utterances
- Quantified by:
  - Percentage agreement: N agreed/N both annotated
  - Cohen's Kappa<sup>1</sup> ( $\kappa$ ): accounts for chance agreement

<sup>&</sup>lt;sup>1</sup>J. Cohen. "A Coefficient of Agreement for Nominal Scales". In: *Educational and Psychological Measurement* 20.1 (Apr. 1960), pp. 37–46.

## Inter-annotator agreement



#### Overall pairwise agreement between annotators

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

<sup>&</sup>lt;sup>1</sup>J. R. Landis and G. G. Koch. "The measurement of observer agreement for categorical data." In: *Biometrics* 33.1 (1977), pp. 159–174.

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- Rather low agreement ("fair" mean κ)
- Large variability among annotators, not explained by L1/expertise
- Single gold-standard label selected for each utterance

<sup>&</sup>lt;sup>1</sup>J. R. Landis and G. G. Koch. "The measurement of observer agreement for categorical data." In: *Biometrics* 33.1 (1977), pp. 159–174.

#### Error distribution

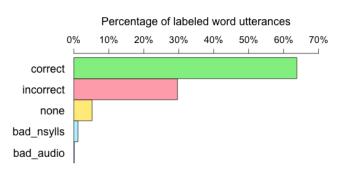


How frequently are errors actually produced by French learners of German?

#### Error distribution



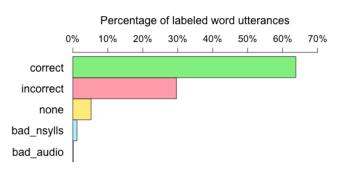
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#### Error distribution



How frequently are errors actually produced by French learners of German?



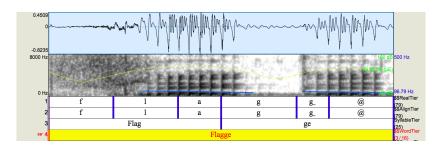
- Large variability across word types
- Beginners made more errors (vs. advanced)
- Children made more errors (vs. adult beginners)

## Word prosody analysis



Requires word, syllable, and phone segmentations

- Automatically produced via forced alignment<sup>1</sup>
- This work uses existing IFCASL segmentations
- Syllable segmentations derived from words & phones



<sup>&</sup>lt;sup>1</sup>L. Mesbahi et al. "Reliability of non-native speech automatic segmentation for prosodic feedback." In: *SLaTE*. 2011.

## Word prosody analysis: Duration



#### Duration (DUR)

- Perceptual correlate: length/timing
- Best indicator of German stress<sup>1</sup>
- Simple to extract from segmentations
- ► Features: Relative syllable & nucleus (vowel) lengths

<sup>&</sup>lt;sup>1</sup>G. Dogil and B. Williams. "The phonetic manifestation of word stress". In: *Word Prosodic Systems in the Languages of Europe*. Ed. by H. van der Hulst. Berlin: Walter de Gruyter, 1999. Chap. 5, pp. 273–334.

## Word prosody analysis: F0



#### Fundamental frequency (F0)

- Perceptual correlate: pitch
- 2nd best indicator of stress after duration<sup>1</sup>
- ▶ Pitch contours computed using JSnoori<sup>2,3</sup>
- Features: relative syllable & nucleus:
  - Mean F0 (in voiced segments)
  - Maximum F0
  - Minimum F0
  - F0 range (max-min)

<sup>&</sup>lt;sup>1</sup>G. Dogil and B. Williams. "The phonetic manifestation of word stress". In: *Word Prosodic Systems in the Languages of Europe*. Ed. by H. van der Hulst. Berlin: Walter de Gruyter, 1999. Chap. 5, pp. 273–334.

<sup>&</sup>lt;sup>2</sup>isnoori.loria.fr

<sup>&</sup>lt;sup>3</sup>J. Di Martino and Y. Laprie. "An efficient F0 determination algorithm based on the implicit calculation of the autocorrelation of the temporal excitation signal". In: *EUROSPEECH*. Budapest, Hungary, 1999, p. 4.

## Word prosody analysis: Intensity



#### Intensity (INT)

- Perceptual correlate: loudness
- Worse predictor than DUR or F0, but still may have effect on stress perception<sup>1</sup>
- Energy contours computed using Jsnoori
- Features: relative syllable & nucleus:
  - Mean energy (over 60dB "silence threshold")
  - Maximum energy

<sup>&</sup>lt;sup>1</sup>A. Cutler. "Lexical Stress". In: *The Handbook of Speech Perception*. Ed. by D. B. Pisoni and R. E. Remez. 2005, pp. 264–289.

## Diagnosis by comparison



#### Comparison to a single reference utterance



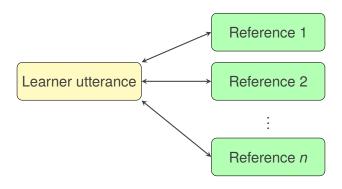
- Simplest approach, common in CAPT
- JSnoori (and predecessors) use this method<sup>1</sup>
  - Assigns 3 scores (DUR, F0, INT)
    - Same syllable stressed?
    - ▶ Difference between stressed/unstressed syllables similar enough?
  - Overall score = weighted average of 3 scores
- Problem: extremely utterance-dependent!

<sup>&</sup>lt;sup>1</sup>A. Bonneau and V. Colotte. "Automatic Feedback for L2 Prosody Learning". In: *Speech and Language Technologies*. Ed. by I. Ipsic. InTech, 2011.

## Diagnosis by comparison



Comparison to multiple reference utterances



- Less common in CAPT systems
- ► Less utterance-dependent than single comparison
- Overall score = average of one-on-one scores

## Diagnosis by comparison



#### Options for selecting reference speaker(s)

- Manually
  - · Learner's choice
  - Teacher/researcher's choice
- Automatically
  - May be more effective to choose reference speaker most closely resembling the learner<sup>1</sup>
  - Selected by comparing speakers' F0 mean and range (using all available recordings)

<sup>&</sup>lt;sup>1</sup>K. Probst et al. "Enhancing foreign language tutors - In search of the golden speaker". In: *Speech Communication* 37.3-4 (July 2002), pp. 161–173.



- More abstract representation of L1 pronunciation
- Not yet explored for German CAPT

#### Research questions:

- How well can lexical stress errors be classified?
- How does that compare with human agreement?
- Which features are most useful for classification?



#### **Experiments:**

- ▶ Trained CART classifiers using WEKA toolkit¹
- Used error-annotated dataset for training/test data (gold-standard labels)
- Used L1 utterances of the same words as training data (all automatically labeled [correct])

#### Evaluated in terms of:

- % accuracy (% agreement with gold-standard labels)
- $\blacktriangleright$   $\kappa$  with respect to gold standard

<sup>1</sup>www.cs.waikato.ac.nz/ml/weka

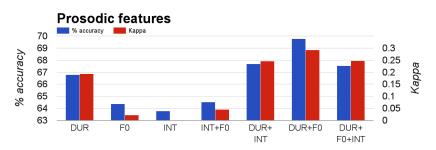


Which features are most useful for classification?

Feature set	Description
DUR F0 INT	Duration features Fundamental frequency features Intensity features
WD LV AG	Uttered word (e.g. <i>Tatort</i> ) Speaker's skill level (A2 B1 B2 C1) Speaker's age/gender (Girl Boy Woman Man)

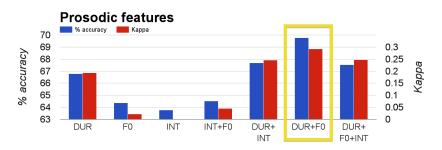


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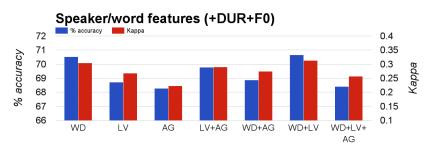


Best performance using only prosodic features: DUR+F0

- ▶ % Accuracy: 69.77%
- κ: 0.29

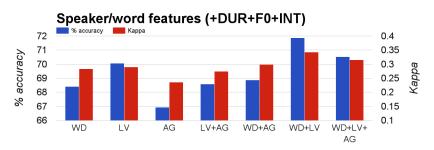


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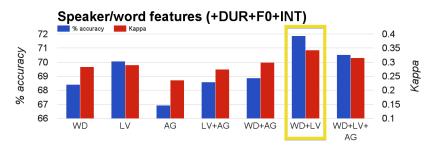


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Best performance overall: WD+LV+DUR+F0+INT

- % Accuracy: 71.87%
- **κ**: 0.34



How does classification accuracy compare with human agreement?

	% agreement	κ
Best classifier vs. gold standard	71.87%	0.34
Mean human vs. human	54.92%	0.23

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

## Implicit feedback



Allows learner to notice features of their utterance/reference utterance, without explicitly evaluating their pronunciation

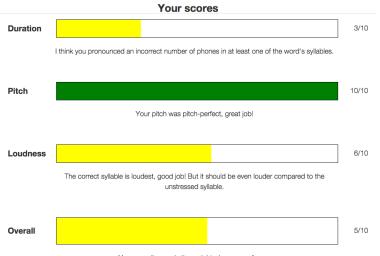
Im Frühling fliegen Pollen durch die Luft.



## Explicit feedback



# Directly calls learner's attention to error(s) and/or offers corrective instruction



#### Self-assessment as feedback



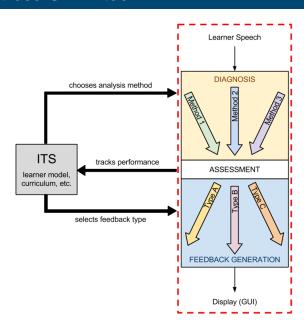
### May be linked to progress and motivation<sup>1</sup>

Self-	assessment		
Listen to	your utterance and the reference utterance(s).		
Then an	swer these questions:		
Which	syllable did you stress?		
0	The first syllable (correct)		
0	The second syllable (incorrect)		
0	Neither syllable (incorrect)		
Is the s	Is the stress as clear in your utterance as it is in the reference utterance?		
0	Just as clear as in reference		
0	Not as clear as in reference		
0	I don't know		
What c	What could you work on for next time?		
	Continue		

<sup>&</sup>lt;sup>1</sup>A. Neri et al. "The pedagogy-technology interface in computer assisted pronunciation training". In: *Computer Assisted Language Learning* (2002).

#### The de-stress CAPT tool



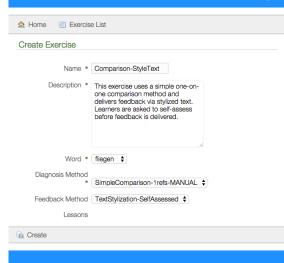


#### Teacher/Researcher interface



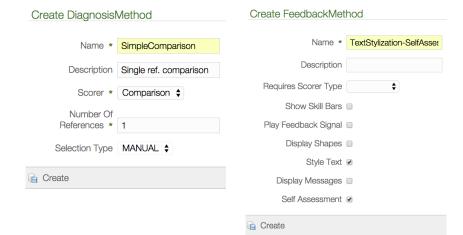
## de-stress





#### Teacher/Researcher interface





#### Student interface









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  - Rather low inter-annotator agreement
  - Roughly one-third of utterances contained errors



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  - 71.87% accuracy,  $\kappa$  = 0.34 wrt. gold-standard labels
  - Slightly better than mean inter-annotator agreement



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  - Integrates various diagnosis and feedback methods
  - Allows teachers/researchers control over methods used



#### Main contributions of the thesis:

- Annotation & analysis of lexical stress errors in small corpus of German spoken by French speakers
  - Rather low inter-annotator agreement
  - Roughly one-third of utterances contained errors
- Exploration of classification for error diagnosis
  - 71.87% accuracy,  $\kappa$  = 0.34 wrt. gold-standard labels
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#### Future work:

- In vivo studies using de-stress
- ► Improve classification performance (e.g. new algorithms)