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[1]

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

- German: variable stress placement, contrastive stress[1]
- French: no word-level stress, final syllable lengthening[2]

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

[1] A. Cutler. "Lexical Stress". In: *The Handbook of Speech Perception*. Ed. by D. B. Pisoni and R. E. Remez. 2005, pp. 264–289.

[2] 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.

Outline

Motivation

Lexical stress errors by French learners of German
- Annotation of a learner speech corpus
- Inter-annotator agreement
- Frequency & distribution of errors

Diagnosis
- Word prosody analysis
- Diagnosis by comparison
- Diagnosis by classification

Feedback
- Implicit
- Explicit
- Self-assessment

The de-stress CAPT tool

Motivation [TODO move before outline?]

Figure: Criteria for selecting errors to target in a CAPT system.

Motivation [TODO remove?]

Lexical stress errors seem to be:

- Frequently produced by French learners of variable-stress languages[1,2]
- More important for intelligibility in L2 German than other types of errors[3]
- Possible to identify automatically by comparison[1] or classification[4]

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[1] A. Bonneau and V. Colotte. "Automatic Feedback for L2 Prosody Learning". In: *Speech and Language Technologies*. Ed. by I. Ipsic. InTech, 2011.

[2] M.-C. Michaux. "Exploring the production and perception of word stress by French-speaking learners of Dutch". In: *Workshop on Crosslinguistic Influence in Non-Native Language Acquisition*. 2012.

[3] U. Hirschfeld. *Untersuchungen zur phonetischen Verständlichkeit Deutschlernender*. Vol. 57. Forum Phoneticum. 1994.

[4] Y.-J. Kim and M. C. Beutnagel. "Automatic assessment of American English lexical stress using machine learning algorithms". In: *SLaTE*. 2011, pp. 93–96.

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

Error annotation

Data: IFCASL corpus of French-German L1/L2 speech[1]

- 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 word utterances by 55-56 L1 French speakers

[1] 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.

Error annotation

15 Annotators, varying by: **[TODO make this a matrix?]**

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

[TODO 5 labels, remove the below]

Each annotated 3 word types in one ∼15 min. session
(1 annotator did 6 word types in 2 sessions)

Error annotation: Method [TODO remove]

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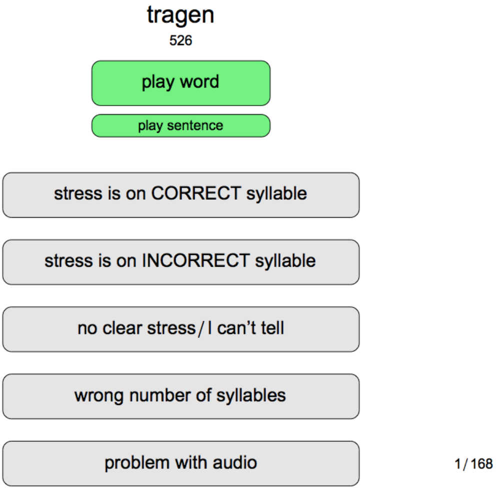
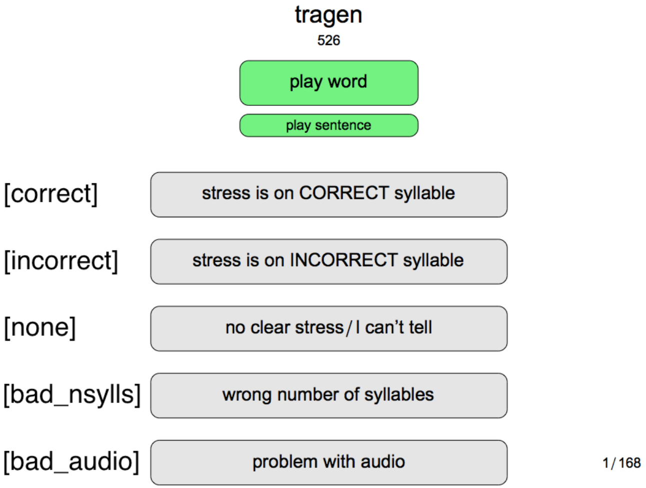
Figure: Praat annotation tool



Error annotation: Method [TODO remove]

Figure: Praat annotation tool



Inter-annotator agreement

How reliably can human annotators identify errors in learner utterances?

- Agreement calculated for each overlapping pair
- Quantified by:
  - Percentage agreement: N agreed/N both annotated
  - Cohen's Kappa[1] (κ): accounts for chance agreement
- **[TODO *remove?*]** Overall agreement represented by mean, minimum, median, and maximum of all pairwise values

[1] J. Cohen. "A Coefficient of Agreement for Nominal Scales". In: *Educational and Psychological Measurement* 20.1 (Apr. 1960), pp. 37–46.

Table: Overall pairwise agreement between annotators

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

- Rather low agreement ("fair"[1] mean κ)
- Large variability between annotators
- Not explained by L1/expertise groups

[1] J. R. Landis and G. G. Koch. "The measurement of observer agreement for categorical data." In: *Biometrics* 33.1 (1977), pp. 159–174.

Choosing gold-standard labels

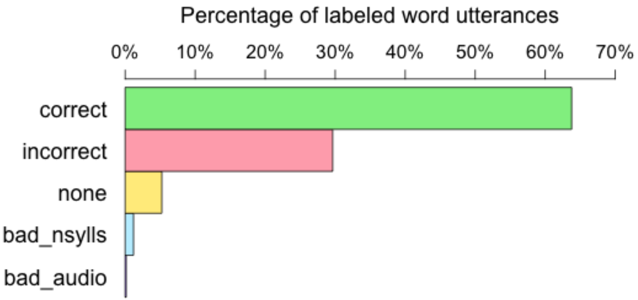
[TODO Find more graphical way to portray this? Remove?]

Need a single label for each utterance to analyze error frequency & evaluate automatic diagnosis

- 268 utterances: no disagreement
- 265 utterances: majority vote
- remaining 135 utterances decided by rules, e.g.:
  - favor Expert judgments
  - favor certainty ([correct],[incorrect]) over [none]
  - be generous to learners if [correct] vs. [incorrect]

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[1]
- This work uses existing IFCASL segmentations
- Syllable segmentations derived from words & phones

[TODO segmentation screenshot]

[1] 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[1]
- Simple to extract from segmentations
- Features: Relative syllable & nucleus (vowel) lengths

[1] 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[1]
- Pitch contours computed using JSnoori[2,3]
- Features: relative syllable & nucleus:
  - Mean F0 (in voiced segments)
  - Maximum F0
  - Minimum F0
  - F0 range (max−min)

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[1] 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.

[2] jsnoori.loria.fr

[3] 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.

Intensity (INT)

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

[1] A. Cutler. “Lexical Stress”. In: *The Handbook of Speech Perception*. Ed. by D. B. Pisoni and R. E. Remez. 2005, pp. 264–289.

[TODO Slide previewing comparison vs. classification?]

Diagnosis by comparison

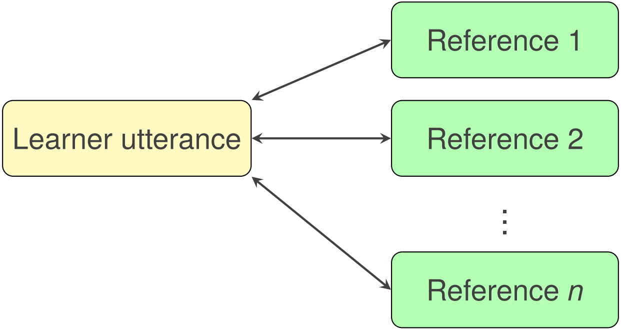
Comparison to a single reference utterance

Learner (L2) utterance $\longleftrightarrow$ Reference (L1) utterance

- Simplest approach, common in CAPT
- JSnoori (and predecessors) use this method[1]
  - 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!

[1] A. Bonneau and V. Colotte. "Automatic Feedback for L2 Prosody Learning". In: *Speech and Language Technologies*. Ed. by I. Ipsic. InTech, 2011.

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[1]
  - Selected by comparing speakers' F0 mean and range (using all available recordings)

[1] 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.

Diagnosis by classification

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- 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?*

Diagnosis by classification

Experiments:

- Trained CART classifiers using WEKA toolkit[1]
- Used annotated L2 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:

- Agreement (%, κ) with gold-standard labels
- Precision, Recall, F_1 and F_2 for [correct] class **[TODO explain and/or put on handout]**

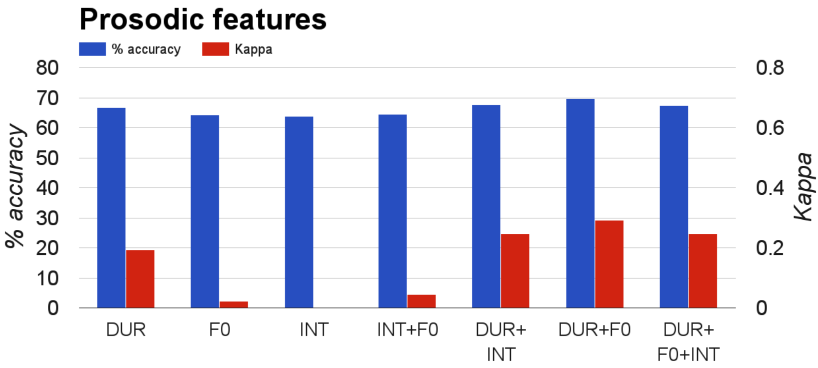
[1] www.cs.waikato.ac.nz/ml/weka

Diagnosis by classification

Which features are most useful for classification?

Feature set	Description
DUR	Duration features
F0	Fundamental frequency features
INT	Intensity features
WD	Uttered word (e.g. *Tatort*)
LV	Speaker's L2 German skill level (A2|B1|B2|C1)
AG	Speaker's age/gender (Girl|Boy|Woman|Man)

How well can lexical stress errors be classified?



Diagnosis by classification [TODO redo chart]

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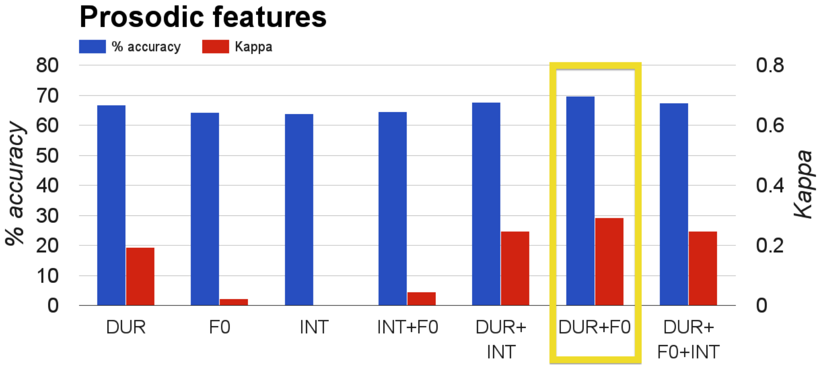
How well can lexical stress errors be classified?



Best performance using only prosodic features: DUR+F0

- % Accuracy: 69.77%
- κ: 0.29

Diagnosis by classification

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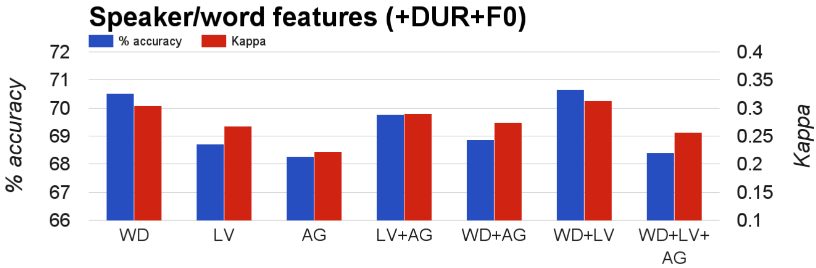
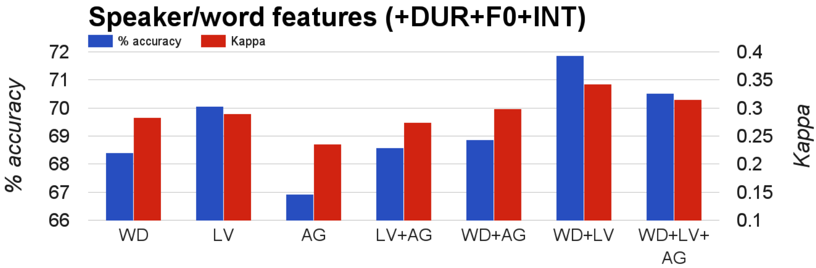


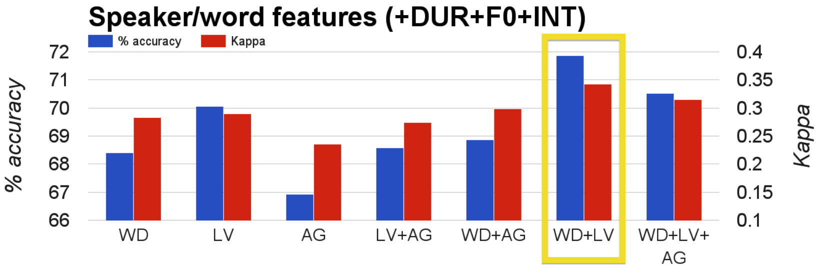
Diagnosis by classification

How well can lexical stress errors be classified?



Diagnosis by classification

How well can lexical stress errors be classified?



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

- % Accuracy: 71.87%
- κ: 0.34

Diagnosis by classification

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

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[TODO]

Explicit feedback

[TODO]

Self-assessment

[TODO]

[TODO]

- Create Exercise
- Create DM
- Create Scorer?
- Create FM
- Show FB output