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

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Some syllable(s) in a word more accentuated/prominent[1]

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

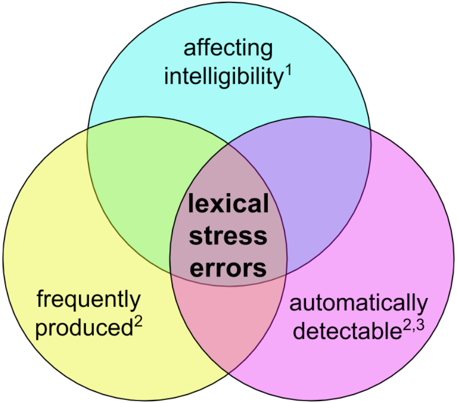
- German: variable stress placement, contrastive stress[1]
- French: no word-level stress, final syllable lengthening[2]

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.

Lexical stress errors in CAPT



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

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

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

- 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

- *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 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 German word utterances by $\sim$55 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.

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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Task: label utterances of 3 word types

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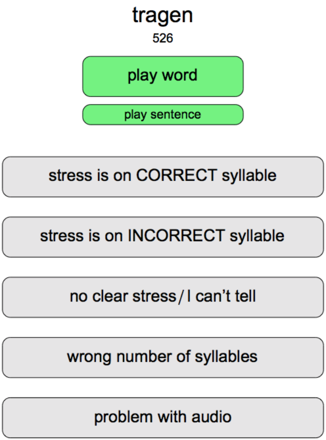

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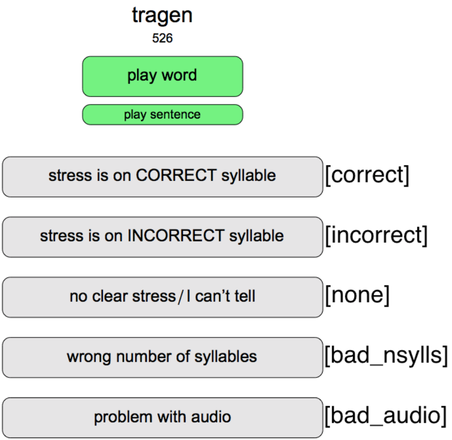

Inter-annotator agreement

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[1] (κ): accounts for chance agreement

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

Inter-annotator agreement

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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

[1] 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"[1] mean κ)
- Large variability among annotators, not explained by L1/expertise
- Single gold-standard label selected for each utterance

[1] 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?

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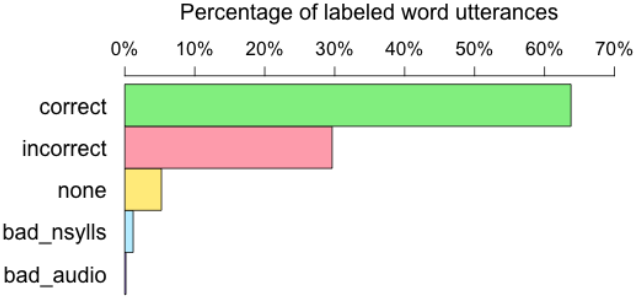

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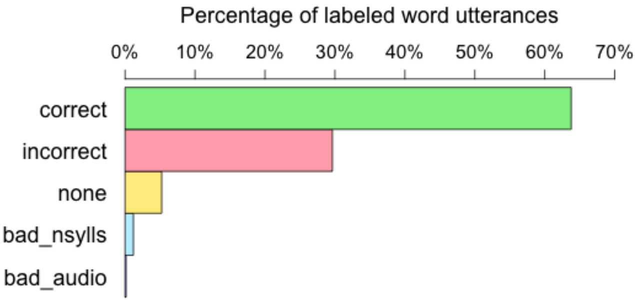
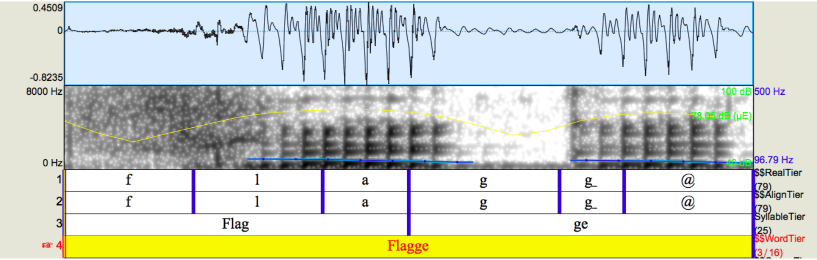


- Large variability across word types
- Beginners made more errors (vs. advanced)
- Children made more errors (vs. adult beginners)

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



[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

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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)

---

[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.

Word prosody analysis: Intensity

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.

Diagnosis by comparison

Comparison to a single reference utterance

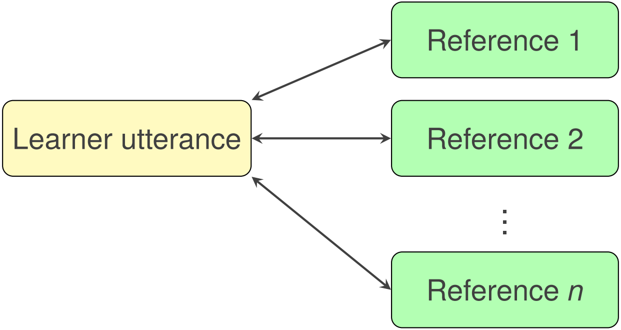
Learner utterance ⟷ Reference (L1) utterance

- 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.

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[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

- 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 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)
- κ with respect to gold standard

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

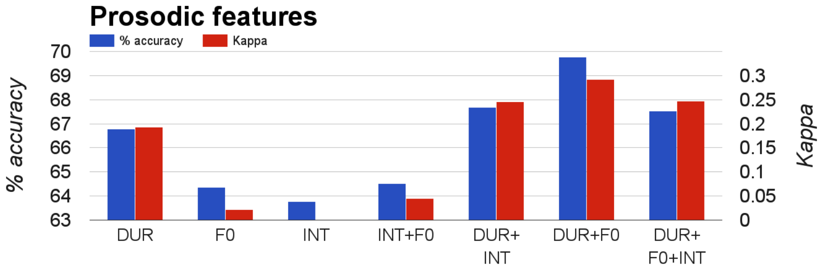
Diagnosis by classification

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 skill level (A2|B1|B2|C1)
AG	Speaker's age/gender (Girl|Boy|Woman|Man)

Diagnosis by classification

How well can lexical stress errors be classified?



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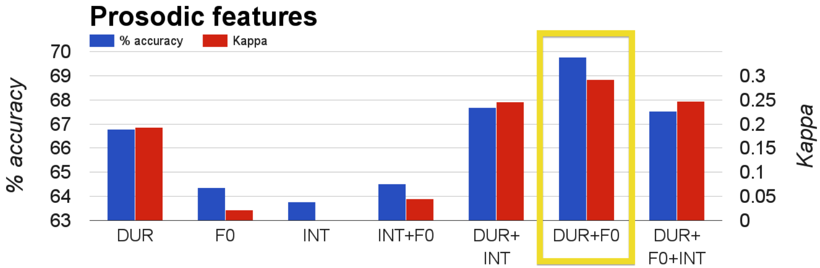

Best performance using only prosodic features: DUR+F0

- % Accuracy: 69.77%
- κ: 0.29

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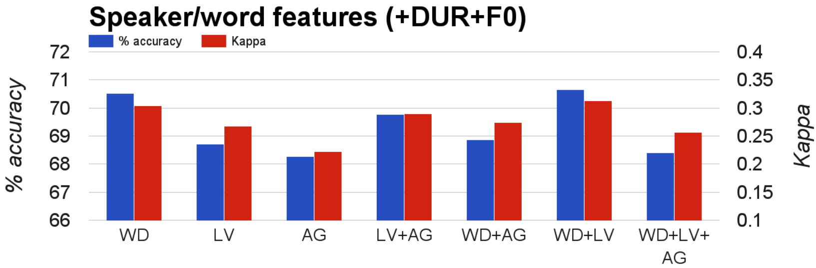

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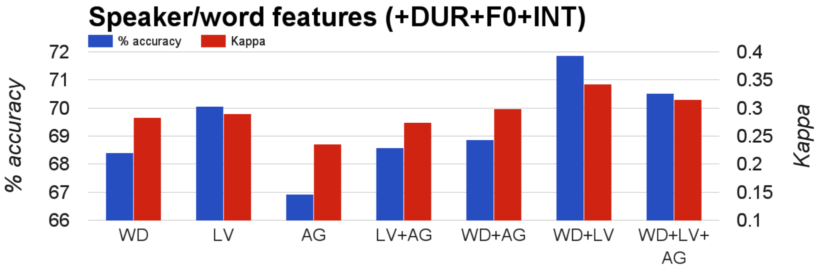

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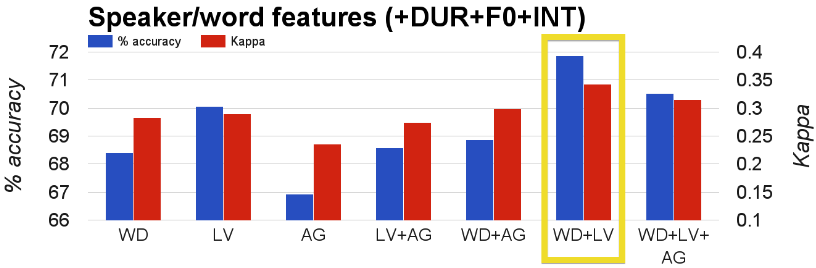


Best performance overall: WD+LV+DUR+F0+INT

- % Accuracy: 71.87%
- κ: 0.34

Diagnosis by classification

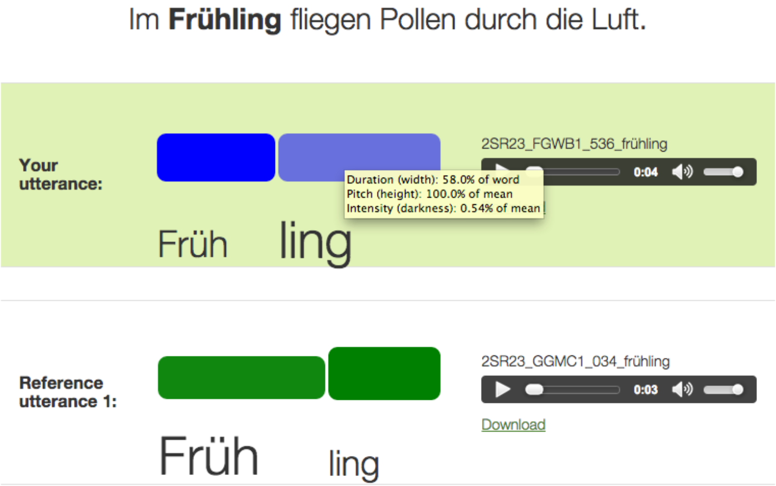
How does classification accuracy compare with human agreement?

	% 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

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



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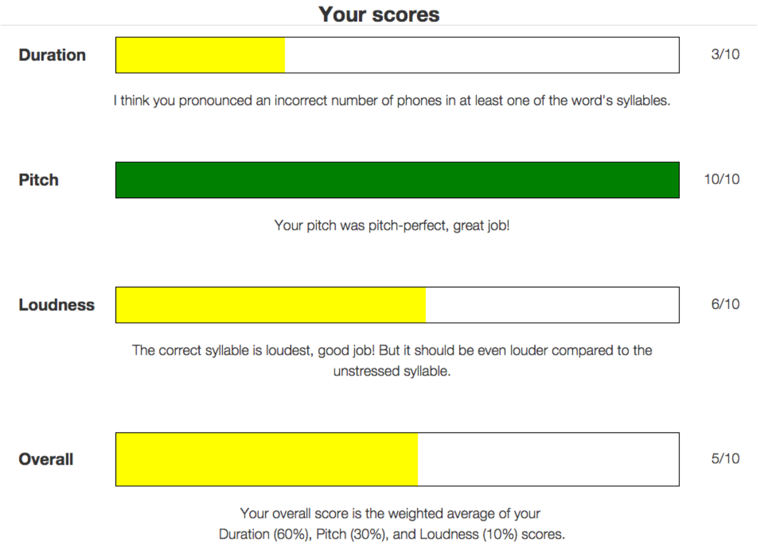
Directly calls learner's attention to error(s) and/or offers corrective instruction



Self-assessment as feedback

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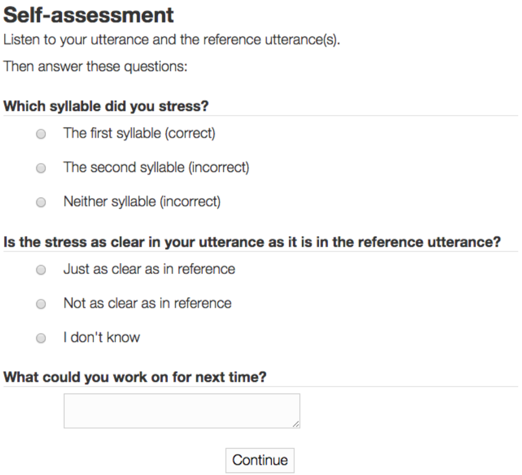
May be linked to progress and motivation[1]



Self-assessment

Listen to your utterance and the reference utterance(s).

Then answer these questions:

Which syllable did you stress?

- The first syllable (correct)
- The second syllable (incorrect)
- Neither syllable (incorrect)

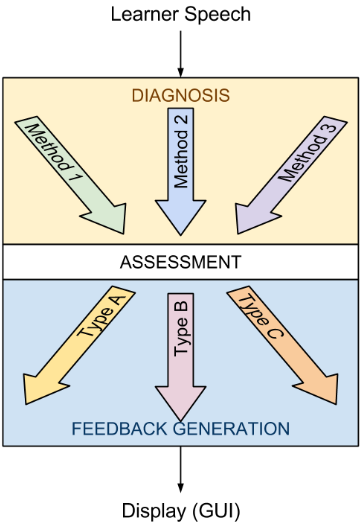
Is the stress as clear in your utterance as it is in the reference utterance?

- Just as clear as in reference
- Not as clear as in reference
- I don't know

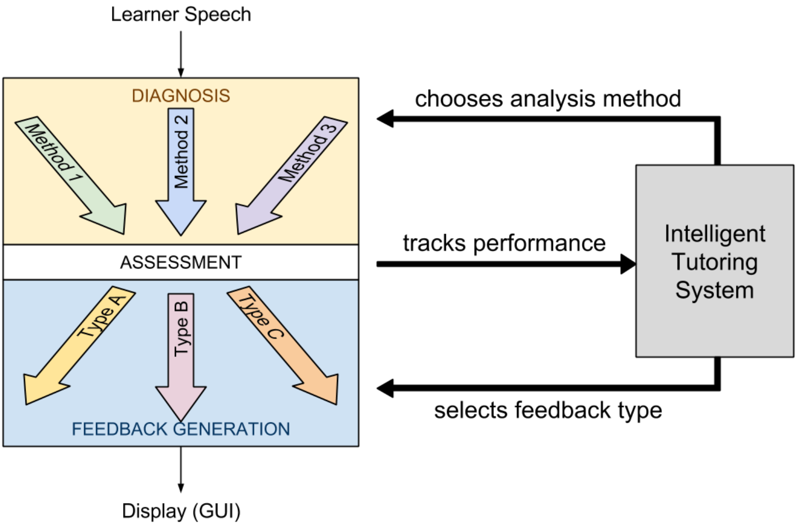
What could you work on for next time?

Continue

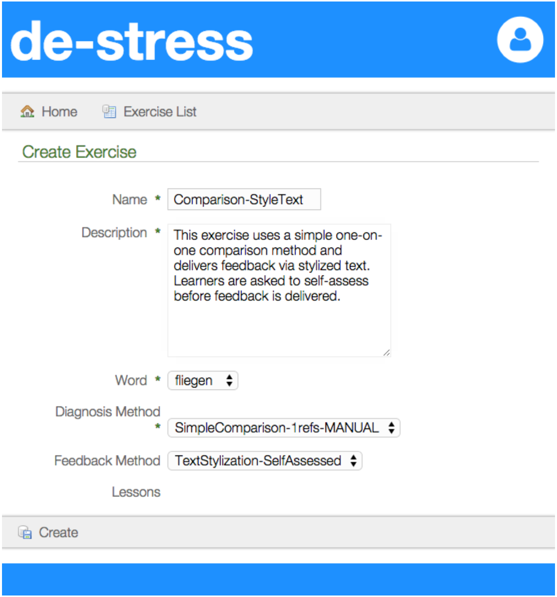
[1] A. Neri et al. "The pedagogy-technology interface in computer assisted pronunciation training". In: *Computer Assisted Language Learning* (2002).


Learner Speech
DIAGNOSIS
Method 1
Method 2
Method 3
ASSESSMENT
Type A
Type B
Type C
FEEDBACK GENERATION
Display (GUI)

de-stress: A prototype CAPT tool



Teacher/Researcher interface



Teacher/Researcher interface

Create DiagnosisMethod

Name * SimpleComparison

Description Single ref. comparison

Scorer * Comparison

Number Of References * 1

Selection Type MANUAL

Create

Create FeedbackMethod

Name * TextStylization-SelfAsses

Description

Requires Scorer Type

Show Skill Bars ☐

Play Feedback Signal ☐

Display Shapes ☐

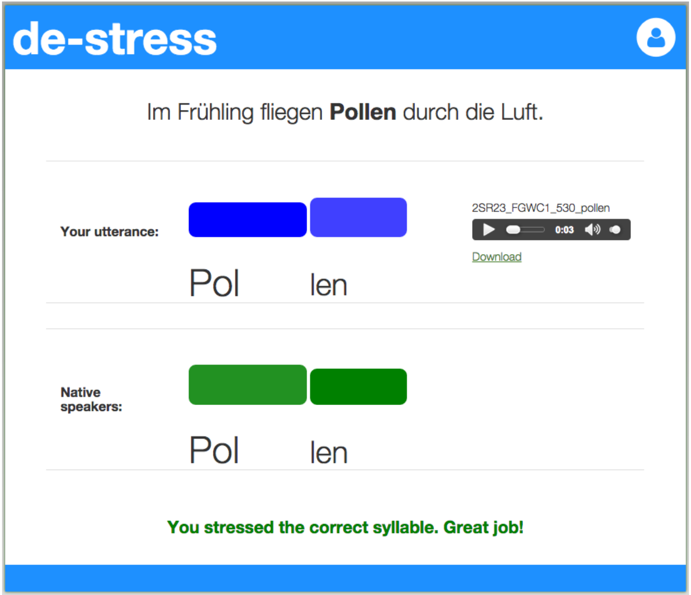
Style Text ☑

Display Messages ☐

Self Assessment ☑

Create

Student interface



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- 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

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Future work:

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