Exploring CEFR classification for German based on rich linguistic modeling

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Introduction

- The Common European Framework of Reference for Languages (CEFR) is an increasingly used standard for
  - characterizing the foreign language ability of a learner
  - based on functional abilities to use language in different domains (public, private, occupational, etc.).
- But there is a lack of
  - authentic learner data illustrating CEFR levels and
  - insight into the precise linguistic characteristics correlating with the proficiency levels.

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Introduction

Towards addressing the desiderata

- MERLIN is creating a learner corpus with CEFR-rated essays for German, Italian & Czech (Abel et al. 2013).
- How can we explore the impact of different aspects of linguistic modeling on the CEFR classification?

⇒ Use machine learning to quantify the value of different linguistic features for automatic proficiency classification.

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Data used: German portion of MERLIN corpus

- 1027 German learner texts
  - about 200 texts per exam type (A1–C1)
  - range of lengths (6–366 words) with average 122 words
  - texts also vary in other parameters:
    - written for different tasks (one of three tasks per level)
    - written by learners with different native languages (> 12)
- Each text was graded in terms of CEFR levels
  - by multiple trained human raters at TELC, a major language test provider in Germany
  - reliability of ratings externally validated (Univ. Leipzig)
  - most common rating: B1

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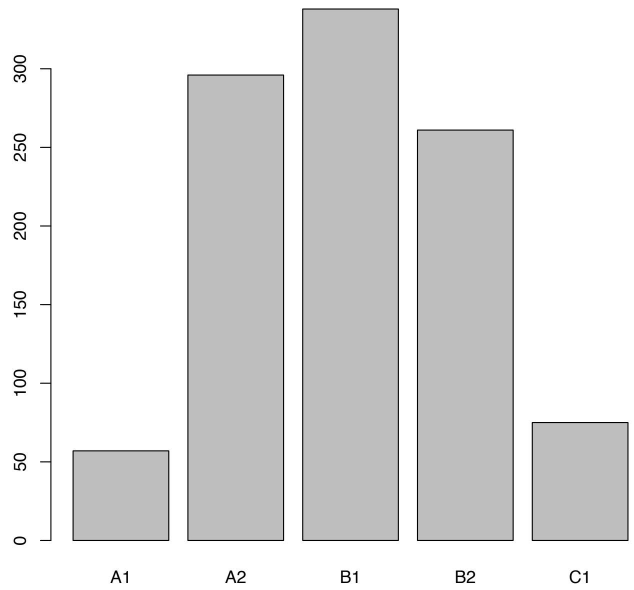
Distribution of Ratings over CEFR levels

Number of texts per essay rating level



Features to be investigated

- Goal: richer linguistic modeling of CEFR levels
  - ⇒ explore potentially relevant language features
  - ⇒ test their impact on predicting CEFR class of each essay
- We explored:
  - lexical features
  - syntactic features
    - statistical language model
    - constituency-based
    - dependency-based
  - morphological features

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Features explored

Lexical features

- Lexical density (Lu 2012)
  - ratio of number of lexical words to total number of words
- Lexical diversity:
  - TTR variants, MTLD, lexical word variation (McCarthy & Jarvis 2010; Crossley et al. 2011a; Lu 2012)
- Depth of lexical knowledge
  - lexical frequency scores (Crossley et al. 2011b)
- Lexical relatedness
  - hypernym & polysemy scores (Crossley et al. 2009)
- Shallow measures
  - spelling errors per number of words, word length

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Features explored

Syntactic features: 1. Statistical Language Models

- inspired by readability assessment research (Schwarm & Ostendorf 2005; Petersen & Ostendorf 2009; Feng 2010)
- used SRILM Language Modeling Toolkit (Stolcke 2002)
- trained on two data sets (Hancke, Meurers & Vajjala 2012)
  - **easy**: 2000 texts, German kid news website *News4Kids*
  - **hard**: 2000 texts, German news channel *NTV* website
- 12 features: unigram, bigram and trigram perplexity for
  - *easy* or *hard* text models based on
  - *word* or *mixed (word+POS)* representations

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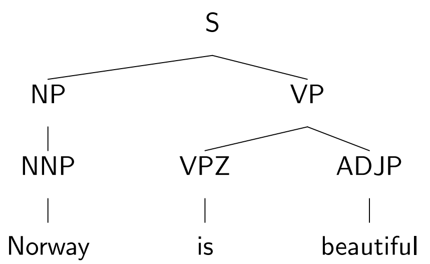
Features explored

Syntactic features: 2. Data-driven constituency features

- Is the frequency of common rules characteristic?
  (Briscoe et al. 2010; Yannakoudakis et al. 2011)
- Extracted all rules in the parse trees assigned by Stanford Parser in 700 articles from the *NTV* corpus
- 

  S → NP VP
  NP → NNP
  VP → VPZ ADJP
- Given a learner text, for each rule, we use as feature:
  rule frequency in text / number of words in text

Features explored

Syntactic features: 3. Theory-driven constituency features

(Hancke, Meurers & Vajjala 2012)

Syntactic properties assumed to be characteristic of complexity or difficulty in SLA proficiency and readability research:

- number and length of
  - clauses, sentences, T-units
  - NPs, VPs, PPs
- dependent clauses and coordinated phrases
  - per clause, sentence, T-unit
- interrogative, relative, conjoined clause ratios
- nonterminals per sentence
- parse tree height

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Features explored

Syntactic features: 4. Theory-driven dependency features

(Vor der Brück et al. 2008; Yannakoudakis et al. 2011; Dell'Orletta et al. 2011)

Linguistic properties based on dependency analysis used in SLA proficiency and readability assessment research:

- number of words between head and dependent
  - maximum
  - average number per sentence
- avg. number of dependents per verb (in words)
- number of dependents per NP (in words)

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Features explored

Morphological features

- Word Formation
  - ratios of nominal suffixes (*-ung*, *-heit*) and compounds
- Inflectional Morphology
  - of verb: person, mood, verb-form (participle, infinitive)
  - of noun: case
- Tense:
  - frequency ratios of verbal tense features
  - data-driven, based on 700 texts from *NTV* corpus

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NLP used for automatic feature identification

- Preprocessing
  - sentence segmentation, tokenization (Apache OpenNLP)
  - spelling correction (Java API for Google Spell Check)
- Lexicon
  - lexical semantic relations (GermaNet, Hamp & Feldweg 1997)
  - lexical frequencies (dlexDB, http://dlexdb.de)
- Part-of-Speech Tagging
  - POS and lemmatization (TreeTagger, Schmid 1995)
  - fine-grained POS (RFTagger, Schmid & Laws 2008)
- Parsing
  - constituents (Stanford PCFG Parser, Rafferty & Manning 2008)
  - dependencies (*MATE*, Bohnet 2010)

Experimental Setup

- We divided the MERLIN data into
  - training set (721 essays)
  - test set (302 essays)
- We classify into five CEFR classes (A1, A2, B1, B2, C1).
- We use the WEKA machine learning toolkit (Hall et al. 2009) for classification, specifically
  - SMO to train support vector machines (linear kernel)
- Many further experiments → Hancke (2013)

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Performance of different feature groups

Name	#	Accuracy (%)
Random Baseline	-	20.0
Majority Baseline	-	33.0
TENSE	230	38.5
ParseRules	3445	49.0
LanguageModel	12	50.0
SYN	47	53.6
MORPH	41	56.8
LEX	46	60.5

- Informative – but for this data set:
  - Text Length as a single feature: 61.4% accuracy

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Feature Groups Combinations

The best two, three, and four class combinations:

Name	Accuracy
LEX_MORPH	61.1
LEX_TEN	59.8
LEX_LM	59.4
LEX_LM_MORPH	61.1
SYN_LEX_MORPH	58.5
LEX_LM_TEN	57.8
SYN_LEX_LM_MORPH	58.8
SYN_LEX_LM_PR	57.8
LEX_LM_MORPH_TEN	57.8
ALL Features	57.2

- not particularly exciting, but lexical features help

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Feature Selection

- How can we identify the best features?
- The features we use are not independent, so taking the best features using Information Gain is problematic.
- *CfsSubsetEval*: correlation-based feature selection
  - Features that correlate highest with the class but have a low inter-correlation are preferred (Witten & Frank 2005).
- Results:

Name	#	Accuracy
CfsSubsetEval(LEX_LM_MORPH)	30	61.7
CfsSubsetEval(SYN_LEX_LM_MORPH)	34	62.7
CfsSubsetEval(ALL)	88	61.8

Qualitative analysis of the 34 selected features
Syntax

- sophistication of production units
  - avg. sentence length, length of a t-unit
- embedding
  - dep. clause with conj. to dep. clause ratio
- verb phrase complexity
- coordination
- passive voice
- text length

Qualitative analysis of the 34 selected features
Lexicon

- spelling errors
- lexical richness (TTR, MTLD)
- verbal/nominal style (verb variation, noun token ratio)
- lexical sophistication (frequency, easy unigrams, length)

- but: no lexical relatedness features were selected

Qualitative analysis of the 34 selected features
Morphology

- use of derivation (derived nouns/nouns, specific suffixes)
- nominal case (genitive, nominative)
- verbal mood and person (subjunctive, 2. person forms)

Summary

- Automatic proficiency classification: a useful experimental sandbox for exploring the role of linguistic modeling
- Quantitatively difficult but possible to outperform the very high text-length baseline on the new MERLIN corpus.
- Qualitatively insightful analysis of features is feasible.
  - Feature selection helps improve classification results and identify qualitatively interpretable feature groups.
- Outlook:
  - reliable sentence segmentation for learner language needed, crucial for many complexity features
  - analyze impact of learner errors on such analyses, possible using target hypotheses
  - principled exploration of variationist linguistic features (→ talk on Saturday with Julia Krivanek)

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Qualitative analysis of selected features

Detailed Syntax

Interpretation	*Features*
sophistication of production units	avg. sentence length, avg. length of a t-unit
embedding	dep. clauses with conj. to dep. clause ratio, avg. num. non-terminal per words
verb phrase complexity	avg. num. VZs per sentence, avg. length of a VP
coordination	avg. num. co-ordinate phrases per sentence
passive voice	passive voice to sentence ratio
script length	text length

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Qualitative analysis of selected features

Detailed Lexicon

Interpretation	*Features*
lexical richness	type-token ratio, root type-token ratio, corrected type-token ratio, HDD, MTLD
lexical richness w. respect to verbs	squared verb variation 1, corrected verb variation 1
nominal style	noun token ratio
word length / difficulty	avg. num. syllables per word, avg. num. characters per word
lexical sophistication	annotated type ratio, unigram plain easy ratio of words in log frequency band two, ratio of words in log frequency band four
spelling errors	ratio of lex. types not in Dlex, Google spell check error rate

Qualitative analysis of selected features

Detailed Morphology

Interpretation	*Features*
nominalization, use of derivational suffixes and words with Germanic stems	*-keit*, *-ung*, *-werk*, derived nouns to nouns ratio
nominal case	genitive-noun ratio, nominative-noun ratio
verbal mood and person	subjunctive-verb ratio, second person-verb ratio, third person-verb ratio

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