Exploring linguistic complexity in readability analysis and L2 development

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based on joint research with

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Linguistic Complexity

- Aspects of linguistic complexity are used to characterize
  - the increasingly elaborate and varied language produced by learners in **Second Language Acquisition** research
  - which audience can read a text in **Readability** research
  - how hard it is for humans to process sentences (lexical frequency, Dependency Locality Theory, surprisal, . . .)
- Aspects of linguistic complexity not touched on here:
  - comparison of linguistic systems (are some languages more complex than others, recursion, . . .)
  - comparison of linguistic theories (are some analyses less complex than others, . . .)
  - language change (historical development from more to less complex, where does complexity come from?, . . .)

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What is readability analysis?

We want to determine how difficult it is to read

- a given **text**
- for a given **purpose**, e.g.,
  - skimming for information
  - answering comprehension questions
- for a given individual **reader** with
  - their knowledge of the topic domain
  - individual differences in cognition, affect, personality

⇒ Which characteristics of the texts can we consider?

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Traditional approaches to readability

- Long history of readability formulas (DuBay 2004)
  - Developed for specific purposes, e.g., characterizing demands of military training manuals (Caylor et al. 1973)
- Formulas are based on shallow, easy to count features:
  - typically avg. sentence length and avg. word length, e.g., Flesch-Kincaid formula (Kincaid et al. 1975)
  - counts of words on specific word lists (Dale & Chall 1948)
- Problems of traditional readability formulas:
  - based on rough generalizations:
    - long words are rare, long sentences are difficult
  - formulas are domain dependent
  - provide only a quantitative measure, not a characterization of the language aspects involved in readability

What can we observe about a given text?

I. Which language **forms** are used, how are they combined?
- **type** of forms in the **linguistic system**
  e.g.: complex NPs per sentence
- **use** of forms in terms of personal **language experience**, evidence via proxy of representative language records
  e.g.: word frequency, average AoA

II. What type & amount of **meaning** is encoded by the forms, and how is it organized into a coherent discourse?
  e.g.: concreteness, lexical density, referential cohesion

III. What are its demands on **human processing**?
  e.g. memory load for referents, surprisal

What can we observe about a given text?

How can we obtain relevant measures?

I. Which language **forms** are used, how are they combined?
⇒ linguistic observations (complex NPs, embedding, . . .)
→ measures of language proficiency established in SLA
⇒ norms for frequency (SUBTLEX), AoA (crowd sourcing)

II. What type & amount of **meaning** is encoded by the forms and how is it organized into a coherent discourse?
⇒ lexical semantic information in databases (MRC, WordNet), CohMetrix measures of coherence/cohesion

III. What are its demands on **human processing**?
⇒ measures from human sentence processing literature, e.g., surprisal (Boston et al. 2008)

SLA measures of proficiency development

- Second Language Acquisition research has developed a rich inventory of measures for monitoring development.
- Skehan (1989) characterized proficiency in terms of the three dimensions Complexity, Accuracy, und Fluency (CAF, Wolfe-Quintero et al. 1998; Housen & Kuiken 2009)
- **Complexity**:
  *The extent to which the language produced in performing a task is **elaborate** and **varied**.*
  (Ellis 2003, p. 340)

Connecting Readability and L2 Complexity

- How about making use of
  - SLA measures of the **complexity** of **learner language**
  - for determining the **readability** of **native texts**?
- Motivation:
  - profit from rich set of SLA measures operationalizing complexity at all levels of linguistic modeling
  - using the same features to characterize reading texts and language proficiency can make it possible to
    - tailor complexity of input to learner proficiency (i+1)
- Putting the idea to the test:
  - Vajjala & Meurers (2012, 2013, 2014a,b,c), Vajjala (2015)
  - Chen & Meurers (2016a,b)

Testing how well the idea works

A supervised machine learning setup as experimental sandbox

- Take a **corpus** of texts for which reading levels are known.
- Spell out hypotheses which properties matter as **features**.
- Train a machine learning **model**.
  - classification: discrete levels (e.g., beg., int., adv.)
  - regression: continuous levels (e.g., age)
  - ranking: relative level (which of two is easier)
- **Evaluate** model by predicting levels of unseen texts.

Corpus

- Needed: a corpus with gold-standard labels
- Previous work: graded reading material in WeeklyReader
- We compiled the WeeBit corpus (Vajjala & Meurers 2012):

Grade Level	*Age in Years*	*Number of Articles*	*Avg. Number of Sentences/Article*
from WeeklyReader			
Level 2	7–8	629	23.41
Level 3	8–9	801	23.28
Level 4	9–10	814	28.12
from BBCBitesize			
KS3	11–14	644	22.71
GCSE	14–16	3500	27.85

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Features from SLA research

Lu (2010, 2011, 2012) surveyed complexity features used in SLA research, which we select many of our features from.

Lexical Features

- Lexical Variation
  - Type-Token Ratio = *Typ* / *Tok*
    - influenced by text length
  - Measure of Textual Lexical Diversity (MTLD, McCarthy 2005)
    - average number of words needed to reach stable TTR point
- Lexical Density = Tok_{Lex} / Tok
  - Lex = open lexical classes (N, Adj, Adv, V)
- Overall we use: 19 lexical features (16 SLA, 3 others)

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Features from SLA research

Syntactic complexity features

- analyze different units: sentences, T-units, clauses
  - a) mean length per unit
    - e.g., mean length of sentences
  - b) number of occurrences per unit
    - e.g., number of clauses per sentence
  - c) ratios of different subtypes (subordination, coordination)
    - e.g., dependent clauses per clause, . . .
  - d) specific constructions
    - e.g., complex nominals per clause, . . .
- Overall we use: 25 syntactic features (14 SLA, 11 others)

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More Features

- Other syntactic features
  - Average parse tree height
  - Average number of NPs, VPs, and PPs per sentence
  - Mean length of NP, VP, and PP
- Traditional features
  - Traditional Features: avg. word length, sentence length
  - Traditional Formulas: Flesch-Kincaid, Coleman-Liau score
  - Word lists: Academic Word List

Experimental Setup
(Vajjala & Meurers 2012)

- Corpus used for experiment: WeeBit
  - 500 training documents per level
  - 125 testing documents per level
- Features computed using standard NLP tools:
  - OpenNLP part-of-speech tagger
  - Berkeley Parser (Petrov & Klein 2007)
  - Tregex pattern matcher (Levy & Andrew 2006) using definitions from Lu (2010)
- Machine learning setup:
  - classification with five classes (levels 2, 3, 4, KS3, GCSE)
  - explored various algorithms in WEKA:
    - decision trees, support vector machines, logistic regression
    - reporting multi-layer perceptron results

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Results on WeeBit (5 classes)

	Number of Features	Performance Accuracy	RMSE
WeeklyReader: Previous Work			
Feng (2010)	122	74.0%	
Petersen & Ostendorf (2009)	25	63.2%	
P. & O. syntactic features only	4	50.9%	
WeeklyReader (Vajjala & Meurers 2012)			
Replication P. & O. syntactic feat.	4	50.7%	
Our Syntactic Features	25	64.3%	0.37
Our Lexical Features	19	84.1%	0.23
All our Features	46	**91.3%**	0.17
WeeBit (Vajjala & Meurers 2012)			
SLALEX	16	68.1%	0.29
SLASYN	14	71.2%	0.28
SLALEX + SLASYN	30	**82.3%**	0.23
All our Features	46	**93.3%**	0.15
BEST10FEATURES	10	89.7%	0.18

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Ten Best Features (Information Gain)

- Half of the best features are **SLA complexity measures**:
  - mean length of a sentence
  - dependent clause to clause ratio
  - complex NPs per clause
  - modifier variation (proportion of adjectives & adverbs)
  - adverb variation (proportion of adverbs)
- The other features in the Top 10:
  - avg. num. characters per word
  - avg. num. syllables per word
  - proportion of words on Academic Word List
  - num. co-ordinate phrases per sentence
  - Coleman-Liau score

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Extending the feature set

(Vajjala & Meurers 2014a)

- Add more features which are meaningful for sentence-level analysis and comparison.

⇒ Add features on lexical system and language use:

- Morphological properties of a word (from Celex)
  e.g., Is the word derived from a stem along with an affix? *abundant=abound+ant*
- Lexical semantic properties of a word (from WordNet)
  e.g., Avg. number of senses per word
- Psycholinguistic features of words
  e.g., word abstractness, average age-of-acquisition (AoA)

Realization of the extended feature set

(Vajjala & Meurers 2014a)

- Resources:
  - Celex Lexical Database (http://celex.mpi.nl)
  - Kuperman et al. (2012)'s AoA ratings
  - MRC Psycholinguistic database (http://ota.oucs.ox.ac.uk/headers/1054.xml)
  - Wordnet (http://wordnet.princeton.edu)
- Tools:
  - Features computed using:
    - Stanford Tagger (Toutanova, Klein, Manning & Singer 2003)
    - Berkeley Parser (Petrov & Klein 2007)
    - Tregex Pattern Matcher (Levy & Andrew 2006)
  - Machine Learning using WEKA
    - SMOReg algorithm (modeling readability as regression) trained on WeeBit corpus

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Results on standard CCSS corpus

- Common Core State Standards reading initiative of the U.S. education system (CCSSO 2010)
- Reference corpus: 168 texts for grade levels 2–12
- Results (Spearman's rank correlation since scales differ):

System	Spearman
Nelson et al. (2012):	
REAP	0.54
ATOS	0.59
DRP	0.53
Lexile	0.50
Reading Maturity	**0.69**
ETS SourceRater	**0.75**
Vajjala & Meurers (2014a)	**0.69**

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Do the results generalize?

(Vajjala & Meurers 2014c)

- Does the WeeBit **model** generalize to other datasets?

Test set	Spearman
CommonCore	0.69
TASA corpus	0.86

- Impact of genre differences in CommonCore data:

Genre in CommonCore	Spearman
Informative	0.76
Misc.	0.69
Literature	0.51
Speech	0.35

Is the **feature set** informative enough for spoken language?

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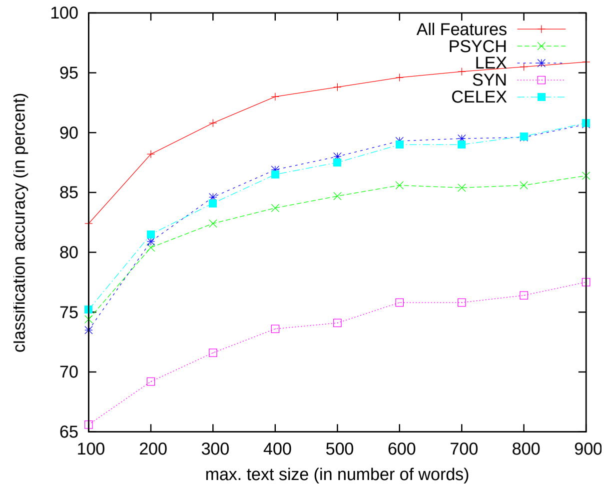
Readability analysis of TV subtitles
(Vajjala & Meurers 2014b)

- We used our feature set to train a model that identifies age-specific TV programs.
- Data: subtitles of BBC TV channels (Van Heuven et al. 2014)
- Classification into three age groups:
  - less than 6, 6–12, adult

⇒ 96% classification accuracy (SMO, 10 fold CV)
  - single most predictive feature: average AoA of words, but accuracy is not reduced if this feature is removed
  - Classification is informed by a wide range of linguistic elaborateness, variedness, and cognitive characteristics.

Effect of Text Size on Classification Accuracy



- Training/testing with longer texts supports higher accuracy.
- But even with 100 words per text, one reaches >80%.
- Lex & Psych best in short texts, Syn more linear increase

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From texts to sentences

- Can we reliably analyze individual sentences?
- This would be useful
  - for text simplification
    - to identify targets for simplification
    - to evaluate aspects of simplification
  - to evaluate sentences in questionnaires
  - to rank candidates in generation systems

→ Test model trained on WeeBit texts on individual sentences

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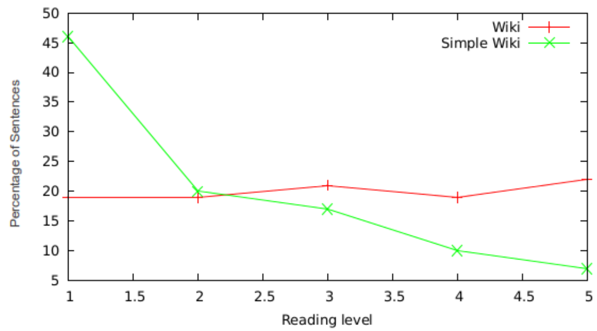
Readability at the sentence level
(Vajjala & Meurers 2014a)

- Test on sentence-aligned Wiki–SimpleWiki (Zhu et al. 2010)
- Predictions of WeeBit text model:



- Simplification is relative: A simplified sentence is simpler than its unsimplified version, but can be harder than another one.
- Hard texts are not simply collections of hard sentences.

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Dealing with the multi-level nature of evidence
Beyond averages

- To classify texts, we rely on evidence at different levels:
  - words, sentences, texts
- What is the best way to combine the evidence?
  - Is computing averages really preserving what is relevant?
- Explored for word frequencies in Chen & Meurers (2016a) using SUBTLEX Zipf scale (Van Heuven et al. 2014)

Dealing with the multi-level nature of evidence
Results on WeeBit (Chen & Meurers 2016a)

- Accuracy of 10-fold CV classification on WeeBit (5 levels):
  - Average frequencies baseline:
    - 24.2% with average token frequency as feature
    - 32.1% with average type frequency as feature
  - Adding Standard Deviation:
    - 39.9% with average token frequency + SD as features
    - 43.3% with average type frequency + SD as features

→ Let's explore different levels of granularity.
  - most informative: characterize a text through the vector of frequencies of every token in the text, but:
    - unlikely to generalize, and
    - texts differ in length

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Dealing with the multi-level nature of evidence
Word frequencies in texts at different levels of granularity

- How about grouping tokens to obtain *n* averages per text?
  i) *n* **frequency bands of the language**
  ii) *n* **clusters of words in document** closest in frequency

  A text is represented by one avg. frequency feature per group.

⇒ This works well for 10-fold CV in WeeBit corpus:
  i) 67.5% accuracy with 90 frequency bands (by types)
  ii) 54.6% accuracy with 100 clusters (by tokens)

- But does this generalize across corpora?
  → Compare WeeBit 10-fold CV with test on CommonCore, reporting Spearman's rank correlation coefficient (ρ)

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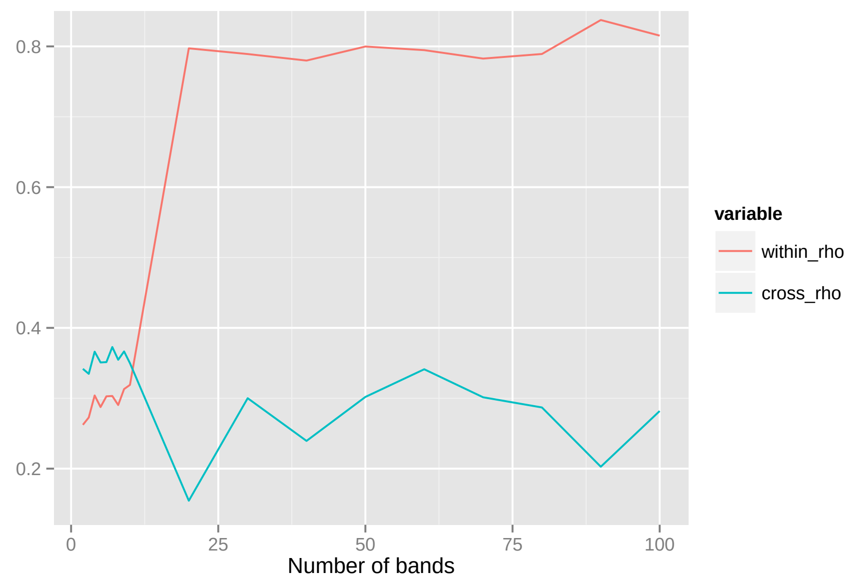
Grouping by frequency bands in the language
Spearman rank correlation within and across corpora



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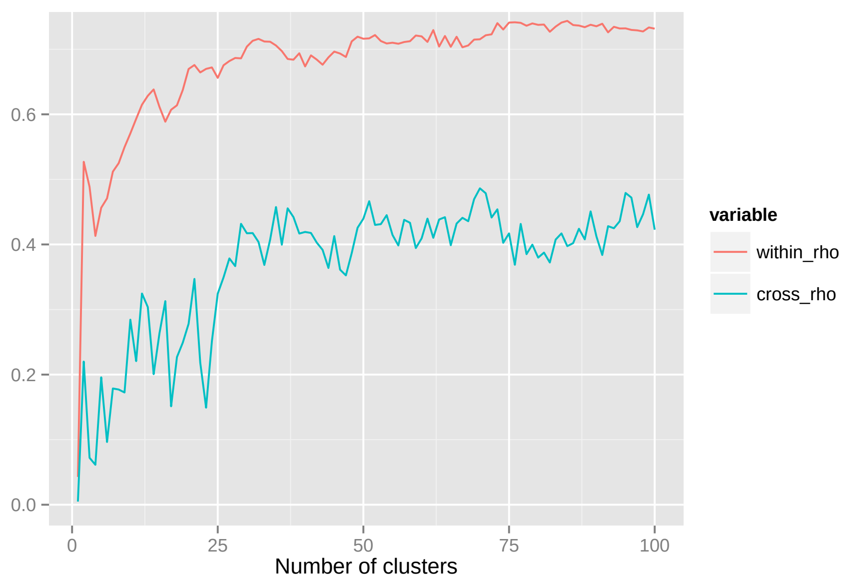
Hierarchical clustering of tokens in document

Spearman rank correlation within and across corpora



Dealing with the multi-level nature of evidence

Summary

- For aggregating word frequencies at the text level:
  - grouping by language frequency band better within-corpus
  - hierarchical clustering of words in text generalizes better
- Conclusion: We should put more thought into how to combine the multi-level nature of the readability evidence.
- Next idea to test:
  - How can the incremental process information provided by Surprisal (Boston et al. 2008) inform text difficulty?
  - → Hierarchical clustering of Surprisal profiles of sentences.

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Using readability to rank web search results

(Vajjala & Meurers 2013)

- Are state-of-the-art readability models actually useful for classifying texts as found on the web?
  - Can we re-rank search results based on reading levels?
- Implementation details:
  - feature set from Vajjala & Meurers (2012)
  - trained model on WeeBit corpus
  - modeling: regression, since we want output on a scale
- We applied the readability model to search results obtained through BING search API.
  - took 50 search queries from a public query log
  - computed reading levels for Top-100 results

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Results: Reading levels of top search results

(Vajjala & Meurers 2013)

Result Rank:	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Avg** Top100
Query:											
copyright copy law	1.8	4.6	1.4	2.7	4.6	6.2	2.7	**1.1**	3.9	5.6	4.6
halley comet	**1.7**	4.5	4.5	4.2	2.4	4.1	4.9	3.6	4.2	3.6	4.0
europe union politics	3.6	4.9	6.3	4.0	2.2	4.5	**1.5**	1.6	4.9	6.3	4.3
shakespeare	2.4	2.9	4.2	4.7	4.7	3.9	**1.5**	2.1	2.6	4.0	3.6
euclidean geometry	3.9	4.7	4.7	4.3	4.5	4.6	4.0	4.1	3.5	**2.6**	3.2
...											

- Avg. reading level of search results quite high (5 = GCSE)
- The model identifies a range of reading levels among most relevant results returned by search engine.
- Readability-based re-ranking of results potentially useful for language-aware search engines in Language Teaching (Ott & Meurers 2010; Chinkina & Meurers 2016)

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Results on WeeBit
Generalizability
Ranking web search
Linking readability & L2 development
Summary
Outlook
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Linking readability and L2 development

- Can we use the complexity features as a looking glass on both readability and L2 development?
  - Idea: Provide texts just above level of student ($i + 1$)
- EFCamDat corpus (Geertzen et al. 2013), prerelease 2:
  - 1.2 million assignments (70 million words)
  - written by nearly 175 thousand learners
  - across a wide range of levels (CEFR A1–C2)

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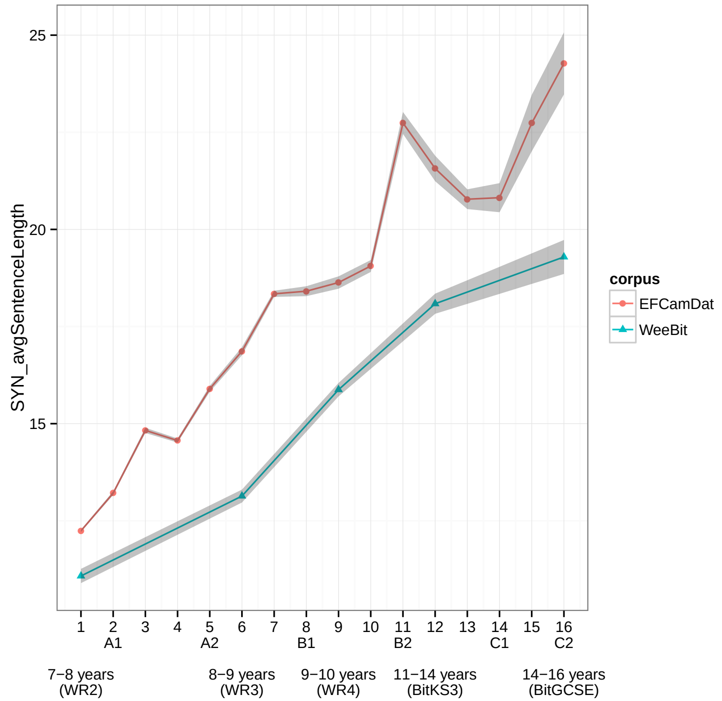
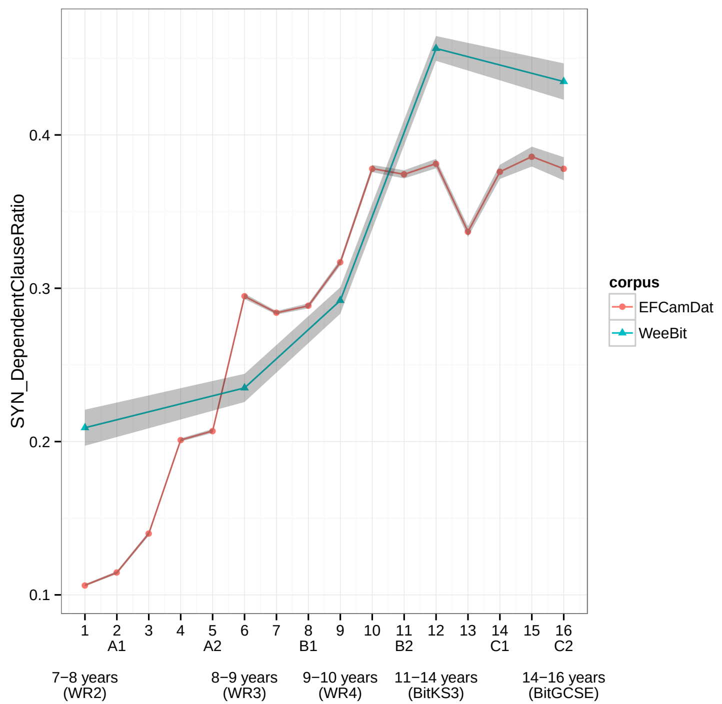
Mean length of a sentence



Exploring linguistic complexity in readability analysis & L2 development

Detmar Meurers

Dependent clause to clause ratio



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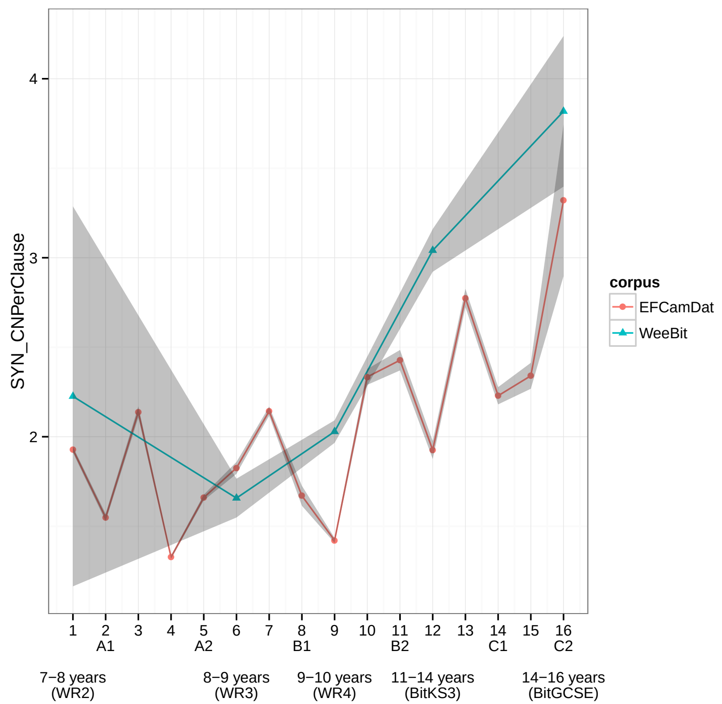
Complex NPs per clause



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Linking readability and L2 development

First conclusions

- Good face validity for using same measures for readability and L2 development.
- Various challenges that need to be addressed, e.g.:
  - impact of analyzing learner language: e.g., variable orthography should not be counted as lexical richness
  - systematic sentence segmentation difficult (both for learner language and certain text types, e.g., CVs)
- Questions to be addressed for selecting $i + 1$ text material:
  - How reliably can we determine reading ability based on measures of writing proficiency?
  - What does the "+1" amount to, for the different aspects of linguistic modeling (lexicon, syntax, ...)?

Summary

- Measures of development from SLA research turn out to be excellent predictors for readability classification.
- Our approach outperforms previously published readability assessment results on WeeklyReader data.
  - best non-commercial readability model on CCSS data
- Feature set generalizes well to other data sets and genres
  - including spoken language transcripts and web data
- Readability reflected in a wide range of linguistic properties
  - Linguistic and cognitive features complement each other.

Summary (cont.)

- Sentence-level analysis:
  - Documents at a given reading level contain sentences at a range of levels of complexity.
  - Readability analysis at the sentence level is feasible, but needs to take the relative nature of readability into account.
- Taking the multi-level nature of the evidence on readability (word, sent., text) into account can support significant gains.
- Approach is applicable to other languages:
  - German readability (Hancke, Meurers & Vajjala 2012) and proficiency (Hancke & Meurers 2013), readability for Bulgarian (Nikolova 2015) and Greek (Georgatou 2016)

Outlook on some current collaborations

- Analyzing linguistic complexity and accuracy in relation to task demands (Alexopoulou, Michel, Murakami & Meurers 2017)
- At interface with empirical educational science (LEAD):
  - Studying the cognitive correlates of readability using eye-tracking (Vajjala, Meurers, Eitel & Scheiter 2016)
  - Is the language in school books appropriate for grade level and school type? ReadingDemands with Berendes & Bryant
  - Linguistic and numerical factors contributing to the complexity of Word Problems (Daroczy et al. 2015)
  - Impact of linguistic complexity of questionnaires (Göllner et al. 2014)
  - CTAP: A Web-Based Tool Supporting Automatic Complexity Analysis (Chen & Meurers 2016a)

http://www.ctapweb.com

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Sentence-level analysis using ranking

Ranking experiments on Wiki-SimpleWiki (Vajjala & Meurers new)

- Employ a Ranking algorithm, as commonly used in information retrieval to rank search results.
- Setup: SVM^{Rank} on Wiki–Simple Wiki (10-fold CV)
- Result: 82.7% accuracy
  - accuracy = percentage of correctly ranked pairs
  - baseline: 72.3% accuracy for Flesch-Kincaid formula
- Do these results generalize to other data?
  → We compiled a new data set from OneStopEnglish.com

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Sentence-level analysis using ranking
OneStopEnglish experiments (Vajjala & Meurers new)

- Texts from *The Guardian* manually rewritten at 3 levels.
- We extracted and aligned 3113 sentences at two levels (OSE2) and 837 across three levels (OSE3), e.g.:

Adv: *In Beijing, mourners and admirers made their way to lay flowers and light candles at the Apple Store.*

Int: *In Beijing, mourners and admirers came to lay flowers and light candles at the Apple Store.*

Ele: *In Beijing, people went to the Apple Store with flowers and candles.*

Sentence-level analysis using ranking
OSE and Cross-Corpus Results (Vajjala & Meurers new)

- Defined separate train and test sets for WIKI and OSE2
- Flesch-Kincaid **baselines**:

TEST	Accuracy
WIKI	69.0%
OSE2	69.6%

- **Same-Corpus Results** of RankSVM model:

TRAIN	TEST	Accuracy
WIKI	WIKI	81.8%
OSE2	OSE2	81.5%

- **Cross-Corpus Results** of RankSVM model:

TRAIN	TEST	Accuracy
WIKI	OSE2	74.6%
OSE2	WIKI	77.5%

$\Rightarrow$ Rich features set supports reliable sentence-level analysis.

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