Automatic Readability Assessment
Features, models and their applicability

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Outline of the Talk

- Background
  - What is readability assessment?
  - Where is it useful?
  - How do we build an automatic model for readability?
- Our Approach
  - Corpus, Features and Modeling
- Applicability to real world
  - for various domains and genres
  - sentences instead of documents
  - practical applications
- Readability Assessment for German

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What is readability assessment?

Measuring **how difficult** it is to read a text,

- given a **purpose**, e.g.,
  - identifying appropriate texts for the readers
  - evaluation of natural language generation systems
- based on **properties of the text** using criteria which are
  - theory-driven (e.g., difficult syntactic constructions)
  - data-induced (e.g., corpora with graded texts)
  - in-between (e.g., derived frequency information for words)
- for a **user**, given some information about him (e.g., language ability, age, working memory)
  - obtained directly (e.g., questionnaire), or
  - indirectly (e.g, inferred from nature of a search query)

Where is this useful?

- retrieving relevant reading materials for language learners (e.g., REAP project, http://reap.cs.cmu.edu)
- evaluating the quality of abstracts and automatically generated summaries (Kanungo & Orr 2009)
- readers with special needs (e.g., adults with intellectual disabilities as in Huenerfauth et al. 2009)
- personalized search (Liu et al. 2004)
- assessing difficulty of questions in survey questionnaires (Lenzner 2013)

Where is this useful?

Our work

- text simplification (Vajjala & Meurers, EACL 2014)
  - application context: bilingual classrooms (project starting in June 2014)
- identifying television programs into age-groups based on subtitles (Vajjala & Meurers, PITR 2014)
- comparing the linguistic complexity of German text books across school types & grades (ongoing project)
- analyzing impact of linguistic complexity of questionnaire data on the results (Göllner et al, GEBF 2014 talk)

How is readability assessment done?
Traditional Approaches

- *Traditional readability formulae* used shallow, easy to quantify features
  - e.g., average sentence length, average word length
  - Kincaid et al. (1975), DuBay (2004), ...
- Some others were based on *lexical measures*
  - e.g., words on specific word lists
  - Chall & Dale (1995), ...
- These approaches are popular even now (e.g., in Word).
- Tools exist for calculating scores using
  - popular formulae (e.g., https://readability-score.com)
  - proprietary approaches (e.g., http://www.lexile.com)

How is readability assessment done?

Computational Approaches

- Language n-gram models
  (Si & Callan 2001; Collins-Thompson & Callan 2004; Petersen & Ostendorf 2009)
- Machine learning using lexical and syntactic features
  (Schwarm & Ostendorf 2005; Heilman et al. 2007; Feng 2010)
- Language specific morphological features
  (Dell'Orletta et al. 2011; Francois & Fairon 2012; Hancke et al. 2012)
- Features motivated by cognitive perspective
  (Crossley & McNamara 2011)
- Features motivated by Second Language Acquisition (SLA)
  - measures of language development or proficiency can successfully be used as measures of text complexity
    (Vajjala & Meurers 2012)

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Typical Steps in a Machine Learning Approach

- You have some texts annotated with reading level (**corpus**) or you collect some graded texts.
- Start with a hypothesis about text complexity and quantify the hypothesis (**features**).
- How will you build a machine learning model? (**modeling**)
  - Group it in to discrete readability levels (= classification) e.g., beginner, intermediate, advanced
  - continuous readability levels (= regression) e.g., grade 1, 2, . . .
- Verify the performance (**evaluation**) and use this model for predicting the reading level of new texts.

Our Approach: Overview

- **Corpus**: accessible graded corpora (not created by us)
- **Features**: utilize insights on linguistic complexity from Second Language Acquisition and Psycholinguistics
- **Modeling and Evaluation**: build and evaluate regression and classification models
- **Real-life Evaluation**: test applicability by performing multiple evaluations with real-world test sets

The WeeBit Corpus (Vajjala & Meurers 2012)

We combined two reading level annotated corpora to create a new corpus: WeeBit.

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

Note: If you want to use this corpus for your experiments, please contact me after the talk or send an email later!

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Features from Vajjala & Meurers (2012)

- Lexical Features
  - lexical richness features from Second Language Acquisition (SLA) research
    - e.g., Type-Token ratio, noun variation, . . .
  - POS density features
    - e.g., # nouns/# words, # adverbs/# words, . . .
  - traditional features and formulae
    - e.g., # characters per word, Flesch-Kincaid score, . . .
- Syntactic Features
  - syntactic complexity features from SLA research.
    - e.g., # dep. clauses/clause, average clause length, . . .
  - other parse tree features
    - e.g., # NPs per sentence, avg. parse tree height, . . .

Features from Vajjala & Meurers (2014a)

- Morphological properties of words
  - e.g., Does the word contain a stem along with an affix? *abundant=abound+ant*
- Age of Acquisition (AoA)
  - average age-of-acquisition of words in a text
- Other Psycholinguistic features
  - e.g., word abstractness
- Avg. number of senses per word (obtained from WordNet)

Implementation details

Tools, Resources and Algorithms used

- Tools:
  - For Lexical Features
    - Stanford Tagger (Toutanova, Klein, Manning & Singer 2003)
  - For Syntactic Features
    - Berkeley Parser (Petrov & Klein 2007)
    - Tregex Pattern Matcher (Levy & Andrew 2006)
  - For Machine Learning algorithms
    - WEKA (http://www.cs.waikato.ac.nz/ml/weka/)
    - modeled readability as regression, using SMOReg algorithm.
- 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 Database (http://wordnet.princeton.edu)

How good is our model?

- performance with 10-fold Cross-validation
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  - 168 texts belonging to grade levels 2–12
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System	**Spearman**
Our System	**0.69**
Nelson et al. (2012):	
REAP (http://reap.cs.cmu.edu)	0.54
ATOS (http://renlearn.com/atos)	0.59
DRP (http://questarai.com/Products/DRPProgram)	0.53
Lexile (http://lexile.com)	0.50
Reading Maturity (http://readingmaturity.com)	**0.69**
SourceRater (http://naeptba.ets.org/SourceRater3)	**0.75**

Does this approach work on real-world texts? (Vajjala & Meurers 2014c)

- How well does our readability model generalize?
- Do our features generalize for other datasets?
- Is there a topic or genre effect?
- What happens if we analyze sentences instead of texts?
  - → How accurately can we identify the differences in the sentential reading level before and after simplification?

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Test set	Description	Spearman
CommonCore	168 docs, scale: 2-12	0.69
TASA corpus	37K docs, scale: 28-110	0.86
Math Readability Corpus	120 docs, scale: 1-7	0.29

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Corpus	Description	Pearson	RMSE
WeeBit	625 docs per level, 5 levels	0.92	0.53
CommonCore	168 docs, scale: 2-12	0.59	2.69
TASA	37K docs, scale: 28-110	0.97	1.77
Math Readability	120 docs, scale: 1-7	0.51	1.73

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- Genre-wise performance of our model on the dataset:

Genre	Spearman's Correlation
Speech	0.35
Literature	0.51
Informative	0.76
Misc.	0.69

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- Can this effect be overcome?
  - Yes, by training genre-specific models.
  - → Vajjala & Meurers (2014b)

Tackling the topic or genre effect
(Vajjala & Meurers 2014b)

- We used our feature set to train a model that identifies age-specific TV programs.
- Data: subtitles from 4 BBC channels, that are annotated with three age-groups.
- Result: 96% classification accuracy
- Analysis:
  - single most predictive feature: average AoA of words
  - But accuracy is not reduced if this feature is removed.

  → The classifier is informed by a range of characteristics, not just a single, dominating one.

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- **What happens if we analyze sentences?**

Documents to sentences?

Readability at sentence level

- Does a readability model identify differences between unsimplified and simplified versions of sentences?
- Yes, e.g., consider (sentences from OneStopEnglish.com):

Sentence	**Actual reading level**	**Reading level assigned by our model**
In Beijing, mourners and admirers made their way to lay flowers and light candles at the Apple Store.	*Advanced*	3.6
In Beijing, mourners and admirers came to lay flowers and light candles at the Apple Store.	*Intermediate*	2.3
In Beijing, people went to the Apple Store with flowers and candles.	*Elementary*	1.0

- Why is such sentence level annotation needed?
  - for us: performing and evaluating text simplification

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Readability at sentence level

How do we go about this?

- Can our model detect readability at sentence level?
  → Yes, because we do not have any discourse features.
- How do we do that?
  - Approach 1: train a model on sentence level data.
  - Approach 2: use document level model on sentences.
- Approach 1 did not work well. So we explored approach 2.
  - We first studied the distribution of reading levels between sentence pairs.
  - Later used the scores of a document level model to train a sentence ranking model (work in progress).

Readability at sentence level

Two Datasets

- Sentence aligned Wikipedia–Simple Wikipedia dataset, released by Zhu et al. (2010)
- A three level (advanced/intermediate/elementary) sentence aligned corpus.
  - compiled by us from OneStopEnglish.com, consisting of simplified versions of articles from The Guardian

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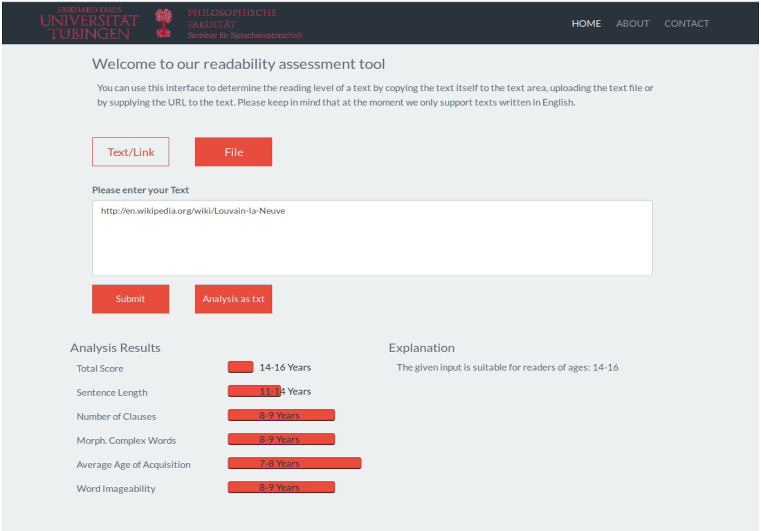
Readability at sentence level

What did we learn? (Vajjala & Meurers 2014a)

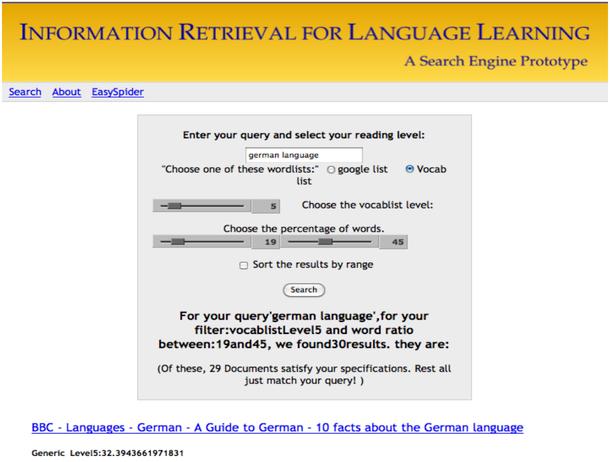
- Simplification is relative
  - → A simplified sentence is simpler than its unsimplified version, but can be harder than another sentence.
- Our approach is particularly successful in classifying the relative reading level of harder sentences.
- It promises to be useful for identifying particularly relevant targets for simplification
  - and to evaluate simplifications given specific readability constraints.

Our Reading level predictor in action



The web-interface is being developed by Ido Friman and will be available soon.

A search engine filtering by vocabulary difficulty



An extension of the Language-Aware Search Engine (Ott & Meurers 2010; Ott 2009).

Readability Assessment beyond English

- Will this approach work for another language?
- Yes, we experimented with German (Hancke et al. 2012).

Readability Assessment for German

Corpus (Hancke, Meurers & Vajjala 2012)

- We created a two class German corpus from two websites containing articles on similar topics:
  - Website for children: GEOlino (http://www.geolino.de)
  - Website for adults: GEO (http://www.geo.de)
  - They are educational monthly magazines covering articles related to technology, nature etc.
  - GEOlino not a simplified version of GEO.
    - Content is created seperately for child readers.
- Modeling: Binary classification.

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Readability Assessment for German

Features and Model evaluation (Hancke, Meurers & Vajjala 2012)

- Features:
  - **General**: lexical, syntactic, language model features
  - **Language specific**: based on inflectional and derivational morphology of German
- Model performance:
  - Binary classification: 90% accuracy
  - Morphological features alone perform at 85% accuracy.

Current and Future Work

- We are working on combining regression and ranking for determining readability at sentence level,
  - and using this information for automatic text simplification.
- Our related projects in LEAD:
  - Analyzing German school text books across grade levels and school types using readability features
    - with Karin Berendes, Detmar Meurers, Doreen Bryant
  - Studying the cognitive correlates of readability using eye-tracking experiments.
    - with Detmar Meurers, Katharina Scheiter, Alexander Eitel
  - Towards Appropriate Reading Material for Bilingual Classrooms: Evaluating the role of linguistic complexity analysis and text simplification in authentic contexts
    - with Detmar Meurers, Kathrin Jonkmann, Jörg-U. Keßler

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Thank you!

- Questions? :-)
- Contact: sowmya@sfs.uni-tuebingen.de
- Bibliography: http://purl.org/net/readability-bib.html

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