Computationally Modeling the Impact of Task-Appropriate Language Complexity and Accuracy on Human Grading of German Essays

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Introduction

- Complexity and accuracy core components in national educational standards for language arts and literacy (CCSSO 2010; KMK 2012)
- Doubts about teachers' ability to evaluate complexity and accuracy of texts (CCSSO 2010; Vögelin et al. 2019)
- Assessed manually in German *Abitur*
  - → Official school-leaving state examination
  - → Determines admission to university
- Study teachers' grading behavior in authentic *Abitur* data

Research Questions and Hypotheses

How do complexity and accuracy influence teachers'

- language performance grades (partial score)?
- content grades (partial score)?
- overall grades (composite score)?

It should be the case that complexity and accuracy

- strongly affect language performance grades
- do not affect content grades
- weakly affect overall grades

Education System in the U.S. and Germany

	U.S. System	German System
Education standard	CCSSO	KMK
High-stakes testing	repeatedly	final examination
Qualitative complexity	teachers	teachers
Quantitative complexity	automatic	teachers
Automatic Testing industry	yes	no

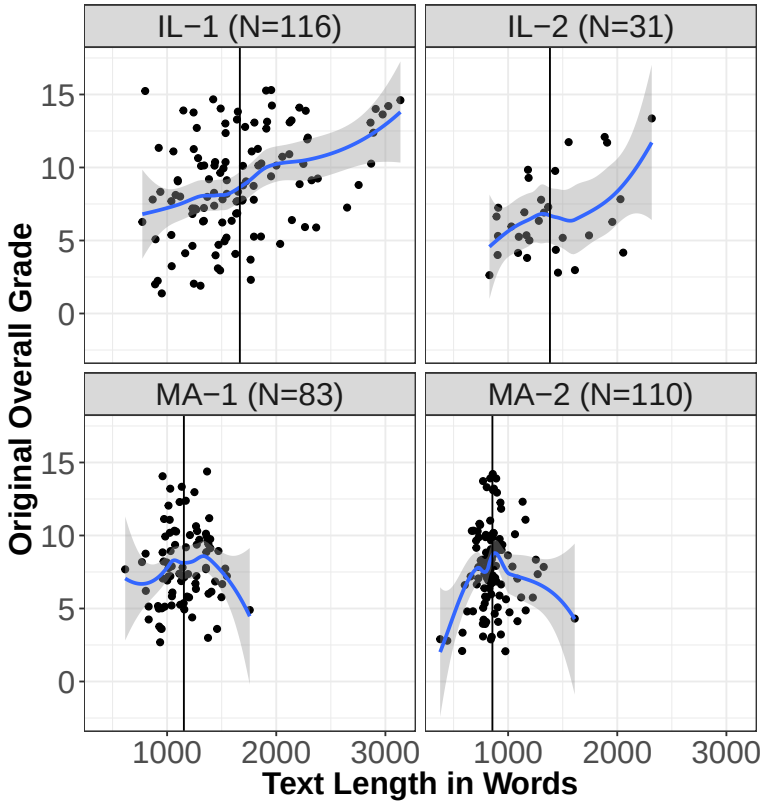
German *Abitur*, Federal States, and the IQB

- *Abitur* = official state examination required for university
- Education is a matter of the German federal states
- The Institute for Educational Quality Improvement (IQB)
  - → monitors schools' adherence to educational standards
  - → provides an official pool of tasks for the *Abitur*
  - → Includes templates for performance requirements
- States may choose and partially alter tasks from the pool

The Data

- Graded essays from German *Abitur* in 2017 ($N = 344$)
- Subject: German literature and language examination
- Collected across German states and digitized by the IQB
- Texts respond to one of four different task prompts
  - → 2 × interpretation of literature (IL-1, IL-2)
  - → 2 × material-based argumentation (MA-1, MA-2)

Task-Effects

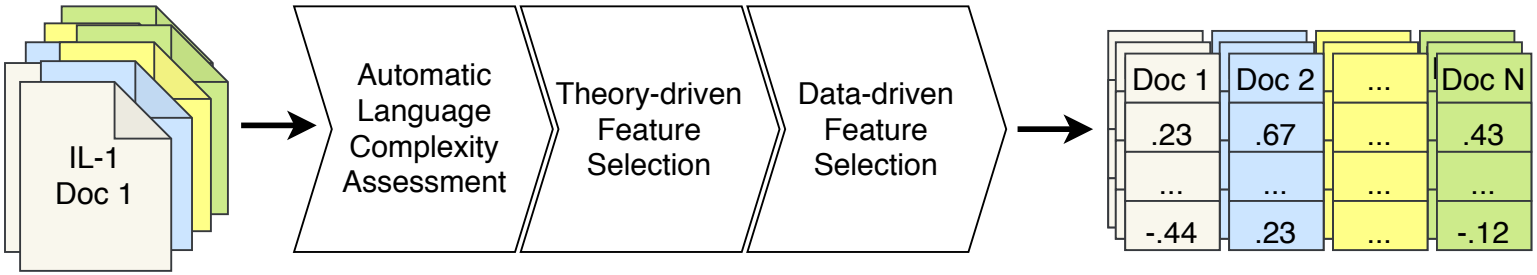


- Task prompts request and elicit texts of different length
- Influences correlation of text length and overall grade
- Task-effects are known to influence linguistic complexity (Alexopoulou et al. 2017; Yoon & Polio 2016)

Selecting and Representing Writing Complexity

- Select authentic texts of more and less task-appropriate overall linguistic complexity for the experiment (±ALC)
- Two-fold strategy:
  1. Build document vector representations capturing relevant dimensions of complexity
  2. Create a ranking of these vector representations to identify more and less complex documents
- Separately for each task to account for task-differences

Step 1: Creating Complexity Vectors



Student Essays

Building Complexity Vectors

Complexity Vectors

Automatic Complexity Assessment

- Automatically extract 320 complexity features (Weiss 2017)
- Successfully used to assess German readability and L1/L2 development (Weiss & Meurers 2018, 2019, in press)
- Measures of human processing, language use, and lexical, morphological, syntactic, and discourse complexity
- Based on SLA research where Complexity, Accuracy, and Fluency are dimensions of language performance (Bulté & Housen 2012; Wolfe-Quintero et al. 1998)

Theoretically-Motivated Complexity Features

- Education standards name examples of welcome writing strategies to make language more complex (KMK 2012)
- Includes argumentation structure, lexical complexity, and syntactic complexity (as well as accuracy)
- Register and norm-appropriateness → academic language (Hennig & Niemann 2013; Snow & Uccelli 2009)
- We identify 75 theoretically-motivated complexity features that are extracted by the system

Theory- and Data-Driven Feature Selection

1. Automatic extraction of 320 complexity features
2. Outlier removal and z-score calculation
3. Calculate the Pearson correlation (r) of each complexity feature with essays' original overall grade (r_g)
4. Add theoretically-motivated feature f ranked by decreasing r_g, if f correlates
   a. $abs(r_g) \geq 0.2$; $p < 0.05$ with the overall grade, and
   b. $abs(r_f) \leq 0.8$ with an already added feature
5. Repeat Step 4 for all other features with $abs(r_g) \geq 0.3$

Theory- vs. Data-Driven Feature Contribution

Task	Theory-Driven	Data-Driven	Total
IL-1	20	13	33
IL-2	32	13	45
MA-1	13	0	13
MA-2	9	4	13

- Resulting complexity vectors differ in length
- Most pronounced differences between task objectives (interpretation of literature, material-based argumentation)
- Overall mostly theoretically-motivated features selected

Zooming in on Complexity Vectors

Feature	IL-1	IL-2	MA-1	MA-2
MTLD	.2014	.4358	.2876	.3361
Dependent clauses per sentence	*.3040*	.2528	.2046	-.0380
Derived nouns per noun phrase	*.2394*	.4751	.1604	.3301
Average total integration cost at finite verb	.4093	*.4909*	.0708	.0308
Complex noun phrases per noun phrase	.4177	*.3186*	.1316	-.0353
Relative clauses per sentence	.3027	.1814	.1381	-.0077
Dep. clauses w/o conjunction per sentence	.1414	.2460	.0744	.0058
Conjunctional clauses per sentence	.1632	.2433	.0744	-.0285

- The four vectors include overall 75 unique features
- 18 features generalize across at least three vectors
- Mostly lexical and clausal complexity and nominal style

→ Known features of German academic language

Differences between Task Objectives and Types

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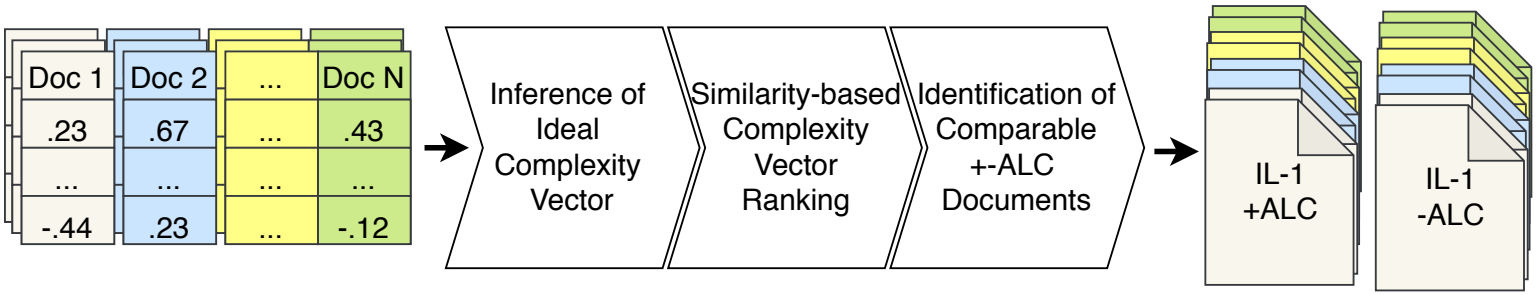
- The interpretation of literature task vectors are similar
- 21/26 features occurring twice are shared by IL-1 and IL-2
- Mostly (noun) phrase complexity and human processing

→ Generalizable characteristics of task objective (interpretation) and type (essay)?

Step 2: Ranking Complexity Vectors



Inferring Task-Wise Ideal Complexity Vectors

- Reference vector identifying the polarity of the correlation
- Assign maximal and minimal feature values to feature dimensions of appropriate and inappropriate complexity
- Positive correlations with original overall grade → 1
- Negative correlations with original overall grade → 0

Document Ranking

- Force each feature in the complexity vectors to range from 0 to 1 using min-max scaling
- Calculate Manhattan distance between each document vector and its corresponding ideal vector
- Rank documents task-wise by increasing distance
- Rank from more to less appropriate language complexity ($\pm ALC$)

Document Selection and Further Processing

- Consider only documents with a medium overall grade → often more difficult to rate and avoids ceiling/floor effects
- Select texts of comparable length from top and bottom rank
  → 16 documents selected (2 +ALC and 2 -ALC per task)
- Manual extraction of punctuation, spelling, and grammar errors by the IQB to assess text accuracy

Teachers Participating in Essay (Re-)Grading

- 33 subjects (14 female, 9 male, 0 diverse)
- Age $\mu = 46.4 \pm 8.7$ years; range = [34; 65]
- Teaching experience $\mu = 19.9 \pm 9.1$ years; range = [5; 38]
- Graded *Abitur* at least twice, mostly more than 8 times

Provided Materials and Grading Set-Up

- Each text was graded by 16 teachers
- Mail with 8 texts without original grades (50:50 $\pm ALC$)
- Grading at home with *Abitur* scale: 0 (worst) to 15 (best)
- Grading template with content and language requirements
- Best approximation of real-life *Abitur* grading

Evaluation

- Linear mixed regression model for each grade
- Response variable: language, content, or overall grade (re-)assigned by teachers in the experiment
- Predictor variables: $\pm ALC$ and z-scores of $\frac{\sum errors}{word}$
- Random intercept for task (IL-1, IL-2, MA-1, MA-2)

Results: Influence on Language Performance Grades

	Estimate	SE	t-value	p-value
(Inter.)	6.989	0.561	12.468	< 0.001
+ALC	1.374	0.368	3.732	< 0.001
Error	-1.992	0.211	-9.459	< 0.001

- +ALC texts get higher language performance grades
- More errors lead to lower language performance grades
- This confirms our expectations as complexity and accuracy are components of language performance

Results: Influence on Content Grades

	Estimate	SE	t-value	p-value
(Inter.)	6.138	0.772	7.948	0.003
+ALC	0.614	0.393	1.562	0.120
Error	-1.265	0.227	-5.586	< 0.001

- No evidence that complexity influences content grading
- More errors lead to lower content grades
- Punctuation, spelling, and grammar errors individually show the same kind of influence
- This partially violates our expectations as complexity and error rate are conceptually unrelated to content quality

Results: Influence on Re-Assigned Overall Grades

	Estimate	SE	t-value	p-value
(Inter.)	6.460	0.696	9.278	0.002
+ALC	0.703	0.359	1.962	0.051
Error	-1.518	0.208	-7.316	< 0.001

- Marginally significant impact of +ALC on overall grades
- More errors lead to lower overall grades
- Corresponding to the results for the partial grades the impact of error rate is over-proportionally strong

Discussion

Complexity

- Language performance grades successfully reflect differences in quantitative complexity
- Grades experienced teachers assign to ecologically valid texts are not unduly influenced by complexity differences
- Earlier findings for teachers in training do not carry over (Vögelin et al. 2019)

Accuracy

- Accuracy influences all grades – even when it is irrelevant
- This is a problematic issue for German *Abitur*
- Confirms Rezaei & Lovorn (2010); Cumming et al. (2002)

Conclusion & Outlook

- First results from collaboration of computational linguistic and education science research
- Novel methodology to identify task-appropriate language complexity for document selection
- Teachers identify and modularize language complexity but are clearly biased by accuracy across all grades
- Future work will investigate further the link between automatic and human complexity assessment and grading

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Task Prompts

Interpretation of literature

- IL-1: Interpretation and comparison of poems
- IL-2: Interpretation of novel ending with given focus

Material-based argumentation

- MA-1: Essay on social media and communication
- MA-2: Comment on dialect use in modern societies

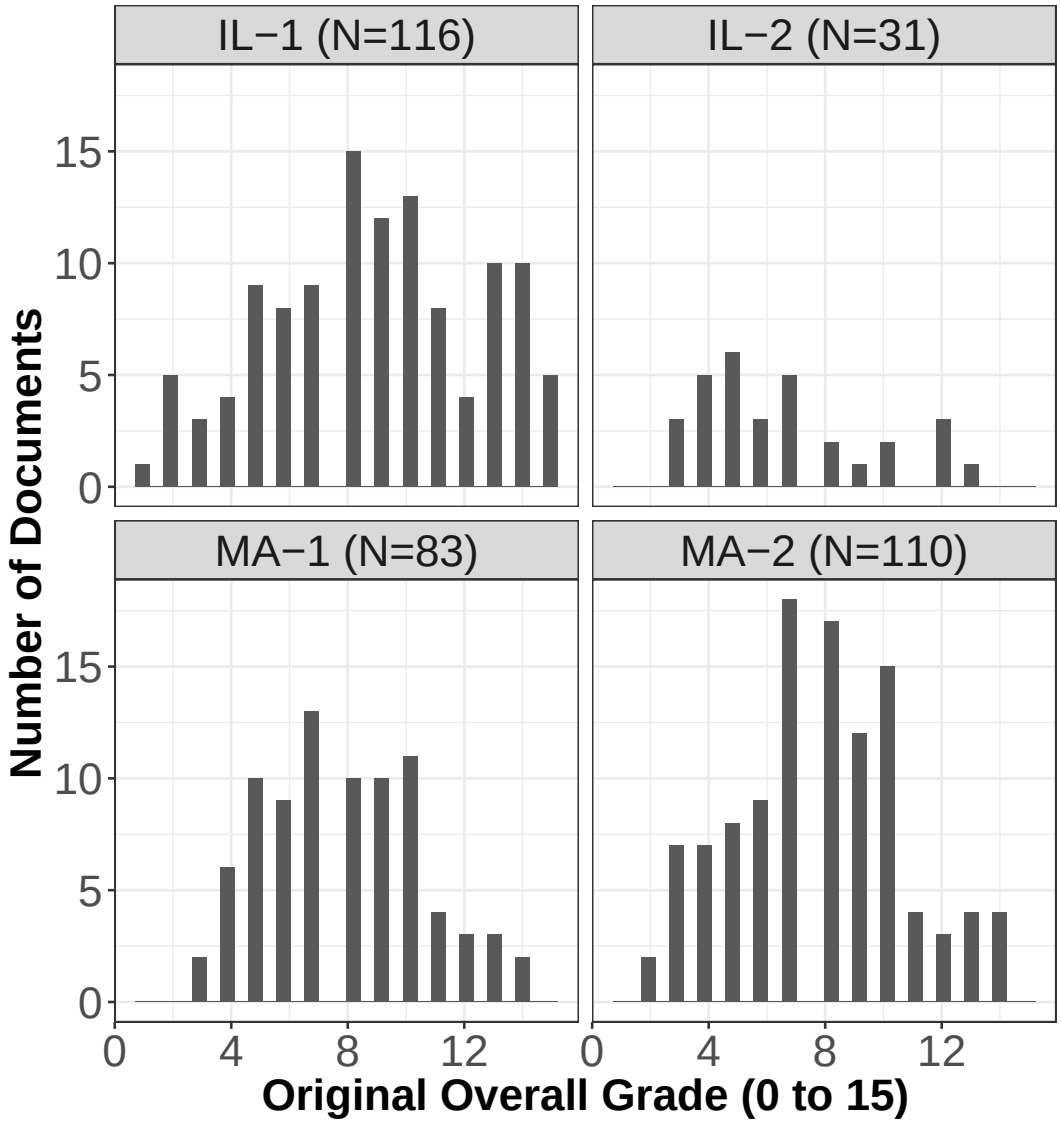
→ Based on 7 to 8 materials (essays, statistics, graphics, ...)

→ Word limits of 1,000 and 800 words

Task Prompts (cont.)

Task	Text Type	Description
IL-1	Interpretation of literature	Interpret poem *A* written in the 1950s and compare it with poem *B* written in the 1980s.
IL-2	Interpretation of literature	Interpret the given excerpt from novel *A*. Focus on the conflicts with which the protagonist struggles.
MA-1	Material-based argumentation	Write a newspaper essay on the influence social media has on our communication. Use around 1,000 words. Include the following materials in your argumentation: 6 essays, 1 poem, 1 statistic.
MA-2	Material-based argumentation	Write a newspaper commentary on the influence of dialects and sociolects on success in society. Use around 800 words. Include the following materials in your argumentation: 4 essays, 1 interview, 2 graphics.

Original Overall Grades Split By Task Prompt



German *Abitur* Grading System

Grade	Points	Percentage
excellent +	15	100–95
excellent	14	94–90
excellent -	13	89–85
good +	12	84–80
good	11	79–75
good -	10	74–70
satisfying +	9	69–65
satisfying	8	64–60
satisfying -	7	59–55
sufficient +	6	54–50
sufficient	5	49–45
sufficient -	4	44–40
insufficient +	3	39–33
insufficient	2	32–27
insufficient -	1	26–20
failed	0	19–0

Content Grades and Spelling Error Rate

	Estimate	SE	t-value	p-value
(Inter.)	5.976	0.802	3.335	0.003
+ALC	0.934	0.444	2.101	0.037
Spelling	-1.197	0.257	-4.651	< 0.001

Content Grades and Grammar Error Rate

	Estimate	SE	t-value	p-value
(Inter.)	5.954	0.392	15.172	< 0.001
+ALC	0.943	0.379	2.489	0.013
Grammar	-1.197	0.257	-4.651	< 0.001

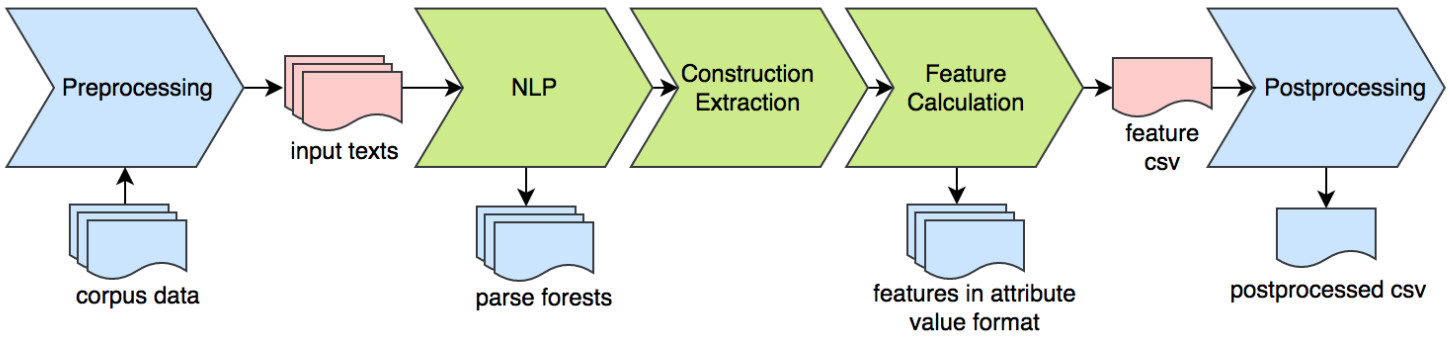
Content Grades and Punctuation Error Rate

	Estimate	SE	t-value	p-value
(Inter.)	6.484	0.534	12.136	< 0.001
+ALC	-0.1016	0.382	-0.266	0.790
Punctuation	-0.5968	0.1939	-3.078	0.002

Complexity in Second Language Acquisition

- Complexity is an important construct in SLA research
- Language performance = Complexity, Accuracy, Fluency (Bulté & Housen 2012; Wolfe-Quintero et al. 1998)
- Complexity = language elaboration and variety (Ellis 2003)
- Accuracy = native speaker-like error rate (Pallotti 2009)
- Fluency = native speaker-like production rate (Pallotti 2009)

NLP Pipeline



Lexical Complexity

- Describes the elaboration, inter-relatedness, and variation of the lexical system
- Measures vocabulary range and size as well as semantic relatedness
- E.g., type token ratio, lexical density, hyponyms per word
- Bulté & Housen (2014); Wolfe-Quintero et al. (1998)

Syntactic Complexity

- Describes the elaboration and variation of the syntactic domain (often split in clausal and phrasal complexity)
- Measures clausal and phrasal modification and variation
- E.g., % dependent clauses types, NP modifiers per NP
- Kyle (2016); Bulté & Housen (2014); Wolfe-Quintero et al. (1998)

Morphological Complexity

- Describes the elaboration and variation of the morphological system
- Measures derivation, composition, and inflection
- E.g., periphrastic tenses per verb, avg. compound depth
- Pallotti (2015); Bulté & Housen (2014); Hancke et al. (2012)

Discourse Complexity

- More elaborate, inter-related, and varied discourse relations are more complex
- Includes measures of cohesive markers, transition probabilities, co-reference chains
- E.g., connectives per sentence, probability subject of drops
- Origin from theoretical and psycho-linguistic research
- Todirascu et al. (2013); Barzilay & Lapata (2008); Graesser et al. (2004)

Language Use

- Assume that less frequently used or later acquired constructions are more complex
- Includes word or phrase frequency measures from large corpora or age of acquisition (AoA) measures
- E.g., mean AoA per word, mean frq. in dlexDB per word
- Origin from corpus- and psycho-linguistic research
- Paquot (2019); Chen & Meurers (2016); Birchenough et al. (2017)

Human Language Processing

- Measures cognitive complexity through processing times as measures by eye-tracking and reading time
- Includes measures of cognitive load and surprisal
- E.g., maximal DLT integration cost per verb
- Origin from cognitive science, psycho-linguistics, and information theory
- Shain et al. (2016); Gibson (2000)