







How well do Student Nurses Write Case Studies? A Cohesion-Centered Textual Complexity Analysis

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Why study writing?

Writing is important for success in school and in the workplace



Over 90% of professionals cite writing as essential in the workplace

Writing is a complex cognitive and social process



Flower & Hayes, 1980; Graham & Perin, 2007; Hayes, 1996; Torrance & Galbraith, 2006

Students underachieve on national tests of writing



Only 25% students in the U.S. exit high school proficient writers

National Assessment of Educational Progress, 2007; 2011

Deliberate Practice



Kellogg & Raulerson, 2007



Computer-based Writing Instruction

- Provides students with *deliberate* practice on their writing
- Rely on automated essay scoring engines to assign:
 - Automated holistic scores
 - Relevant feedback to submitted essays



Allen, Jacovina, & McNamara, 2016

Computer-based Writing Instruction



Computer-based Writing Instruction



Computer-based Writing Instruction



Context

- Measure and quantify the complexity / difficulty of texts
- Present texts of steadily increasing complexity levels to learners
- Dimensions (Common Core State Standards):
 - Quantitative = measurable factors
 - Qualitative = meaning, structure, language conventionality & clarity
 - Reader/task orientation = prior knowledge, motivation & interests

ReaderBench

- Multi-lingual framework integrating advanced NLP techniques
- Provides a *unified vision* of predicting and assessing comprehension for supporting individual and collaborative learning
- Provide a scalable, easily extensible, multi-language platform:
 - English, French, Romanian, Dutch, Spanish, Italian*, Latin*
- Available online: <u>readerbench.com</u>

Multi-dimensional Analysis

- Surface metrics
- Syntax
- Cohesion
- Semantics
- Discourse structure

Surface Analysis

- Readability formulas (Flesch Reading Ease, Gunning's Fog Index, Flesch Grade Level, Dale-Chall)
- Entropy (character, word)
- Fluency (e.g., no. commas, no. words)
- Diction (e.g., word length, *no. syllables/word*, % hard words)
- Structure (e.g., no. paragraphs, size in characters/words/ content words, no. sentences, length)



Word Complexity

- Mean syllable count per word
- Mean polysemy count per word
- Mean distance to the hypernym tree root per word (WordNet)
- Mean difference between the inflected form, the lemma and the corresponding stem, per word
- Age of Exposure



Syntax & Morphology

POS occurences:

- Nouns*
- Prepositions
- Adjectives
- Verbs
- Pronouns*
- Adverbs
- Max depth
- Size of parsing tree
- Semantic dependencies

Cohesion

- An important element of writing quality is text cohesion:
 - Cohesive links or ties between sentences from the same text or fragment of text
- Cohesion is an important element of text processing:
 - Create a unified and connected text
- Consists of local and global cohesion:
 - Local \rightarrow Features that link short text segments of text
 - Global \rightarrow Features that link larger segments of texts

Cohesion versus Textual Complexity

- Mike likes pancakes. The sky is blue. Your favorite cup is on the table.
- Mike likes pancakes. He also likes cake. Cupcakes are John's favorites.
- Mike likes probabilities. He also likes factoring quadratic expressions. Log-linear interpolations are Mike's favorites.
- Cohesion in itself is not enough to distinguish text difficulty
- Lack of cohesion may (artificially) increase textual complexity

Semantics & Discourse

- Cohesion (Inner-block & Intra-block)
- Lexical chains (e.g., max span, avg. span, significance)
- Co-references (e.g., no. chains, chain span)
- Entity-density features (e.g., overlapping nouns, no. entities / unique)
- Discourse connectives
- Word features & vectors from linguistic resources (e.g., LIWC -Linguistic Inquiry and Word Count, ANEW - Affective Norms for English Words, *The General Inquirer: the Harvard IV-4*, *Lasswell*, *SenticNet*, *The Geneva Affect Label Coder*, *EmoLex*)
- Document cohesion flow

* EN only

Document Cohesion Flow

• Automated *cohesion* measures:

- Lexical chains & semantic distances in ontologies Wordnet
- Semantic models: Latent Semantic Analysis [LSA], Latent Dirichlet Allocation [LDA] & word2vec
- Assess semantic global cohesion to capture text organization in terms of paragraph links
- Measure a document's structure derived from the order of paragraphs and of the manner in which they combine to hold the text together
- Develop a number of indices based on
 - *Building criteria*: Maximum value, above the threshold
 - *Ordering*: position and distance accuracy, adjacency accuracy, flow cohesion, correlations, max order sequence

A text with strong cohesion flow should be more coherent

Cohesion Flow using LDA Semantic Similarity



Differences between Essays Scored with High/Low Organization



(b) High organization score

French Experiment

- 40 essay written by 1st-year nurse students:
 - Case studies of infectious diseases and hygiene
 - Mean length: 1,342 words (*SD* = 293);
 - Min: 680 words; Max: 2,179 words
- Semantic models trained on *Le Monde* + 9 textbooks on infectious diseases and hygiene (273 pages ≅ 133,000 words)
- 2 categories: low / high performance students (<13 / ≥13)



Variable Selection

- Removed non-normal indices
- Removed variables that demonstrated multicollinearity (r > .90)
- Levene's test of equality of error variances not significant (p > .05)
- 3 indices chosen (15:1 ratio)
- Regression analysis:
 - One index accounted for 25% of variance in students' essay scores
 F(1, 38) = 12.367, p < .001, r = .496, R² = .246: Document cohesion flow adjacent accuracy using Wu-Palmer distance and maximum criterion

Correlations between *ReaderBench* Textual Complexity Indices and Essay Scores

Indices	r	p
Document cohesion flow adjacent accuracy using Wu-Palmer distance and maximum criterion	.496	.001
Document cohesion flow adjacent accuracy using path distance and above avg + stdev criterion	.451	.004
Content words (i.e., nouns, verbs, adjective and adverbs that are not considered stop-words by providing contextual information)	.448	.004
Average start-middle cohesion using path distance	446	.004
Average paragraph-document cohesion using path distance	436	.005
Average 'voice' paragraph entropy	.431	.005
Average paragraph-document cohesion using Wu-Palmer distance	405	.010

Tests of between-subjects Effects for Significantly Different Indices

Dependent Variable	Mean	Mean	F	Sig.	Partial
	(SD) low	(SD) high			η²
Document cohesion flow adjacent accuracy using	0.98	1.74	17.33	<.001	0.313
Wu-Palmer distance and maximum criterion	(0.61)	(0.54)			
Document cohesion flow adjacent accuracy using	1.07	2.07	18.07	<.001	0.322
path distance and above avg + stdev criterion	(0.63)	(0.85)			
Content words	472.79	655.24	19.16	<.001	0.335
	(122.10)	(139.67)			
Average start-middle cohesion using path distance	0.48	0.41	9.03	.005	0.192
	(0.07)	(0.07)			
Average paragraph-document cohesion using path	0.76	0.74	6.27	.017	0.142
distance	(0.02)	(0.02)			
Average 'voice' paragraph entropy	1.14	1.26	15.15	<.001	0.285
	(0.11)	(0.10)			
Average paragraph-document cohesion using Wu-	0.863	0.855	4.18	.048	0.099
Palmer distance	(0.015)	(0.010)			

Essay Features

Essays with higher scores tend to:

- Be longer & contain more content words
- Introduce more varied concepts, additional ideas (more 'voices')
 => decrease in global cohesion in terms of paragraphdocument cohesion, start-middle cohesion
- Higher entropy = presence of additional semantic chains
- Have a better organization in terms of paragraph structure & a more suitable cohesion flow among adjacent paragraphs => a more coherent discourse.

Discriminant Function Analysis Results

Retained two variables as significant predictors:

- Content words
- Document cohesion flow adjacent accuracy using path distance and above avg + stdev criterion)
- Accuracy: 82.5%, χ²(df = 2, n = 40) = 19.015, p < .001
- LOOCV Accuracy: 77.5%
- Cohen's Kappa of .652 substantial agreement

Discussion

ReaderBench Features:

- Multi-dimensional analysis & Holistic view of AES
- Intense use of NLP techniques
- Integrated an extensible model by combining evaluation factors
- Multi-language support
- Human categorization of professional case studies can be partly predicted by considering document flow features
- Limitations & extensions:
 - Low number of essays
 - Binary essay categorization can be refined with more classes
 - Integrate word specificity measures

The Team behind ReaderBench

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