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I. General Overview

Coh-Metrix is a computational tool that produces indices of the linguistic and discourse representations of a text. These values can be used in many different ways to investigate the cohesion of the explicit text and the coherence of the mental representation of the text. Our definition of *cohesion* consists of characteristics of the explicit text that play some role in helping the reader mentally connect ideas in the text (Graesser, McNamara, & Louwerse, 2003). The definition of *coherence* is the subject of much debate. Theoretically, the coherence of a text is defined by the interaction between linguistic representations and knowledge representations. When we put the spotlight on the text, however, coherence can be defined as characteristics of the text (i.e., aspects of cohesion) that are likely to contribute to the coherence of the mental representation. Coh-Metrix provides indices of such cohesion characteristics.

1. Preliminary information

This document contains a description of 108 indices incorporated into the website Coh-Metrix version 3.0. These descriptions are intended to be succinct specifications for people who want to work on this version of Coh-Metrix. More theoretical information on the Coh-Metrix indices and architecture is reported in Graesser, McNamara, Louwerse and Cai (2004) and Graesser and McNamara (2011). For each level of indices, example scores are provided. However, it is important to note that even small changes in texts can lead to large changes in Coh-Metrix output. It is also important to note that the scores are often subject to the output of third party parsers, lexicons, and word frequency databases, all of which are outside of the control of Coh-Metrix.

2. Coh-Metrix concepts

Some definitions of key concepts are needed to specify the algorithms that underlie the indices in Coh-Metrix 3.0. We define these concepts in this section.

Adjacent versus All sentences

Adjacent sentences are successive sentences in a span of text. For example, if a span of text has 4 sentences, then the adjacent sentences would be sentences 1-2, 2-3, and 3-4. In contrast, *all sentences* are all possible pairs of sentences: 1-2, 2-3, 3-4, 1-3, 1-4, and 2-4. A span of text may be defined in different ways for different purposes, but there is a distinction between paragraph spans and the span of an entire document. The adjacent sentences in Coh-Metrix 3.0 ignore junctures between paragraphs.

Weighted versus Unweighted distances between sentences

This distinction is pervasive in a more advanced version of Coh-Metrix (1.2), but not in most indices used in Coh-Metrix 3.0. When the distance between sentences is weighted, the weight between two sentences decreases the further they are apart in the text. All sentence pairs have equal weight when distances are unweighted. With rare exception, distances between sentences are unweighted in Coh-Metrix 3.0.

Incidence scores versus Ratio scores

An incidence score is the number of classified units per 1000 words. For example, the incidence score for pronouns would compute the number of words that are classified as pronouns for a span of 1000 words. It is equivalent to what some researchers call rates or density scores. In contrast, a ratio score is a relative measure that compares the incidence of one class of units to the incidence of another class of units. For example, a pronoun ratio is the incidence of pronouns divided by the incidence of noun-phrases. Ratio scores compare two different metrics (classes of units) whereas an incidence score applies to only one metric.

Repetition score

A repetition score is computed on sequences of text units that are classified into categories. This score is the proportion of adjacent pairs of units in the sequence that are in the same category. If there are N units in a sequence, there are (N-1) adjacent pairs. The number of adjacent pairs in the same category is divided by N-1. For example, we have computed the repetition score for a sequence of categories A, B, and C:

Category sequence: A B B B C A A C C B B B B A C C

Adjacency repetition 0 1 1 0 0 1 0 1 0 1 1 0 0 1

The repetition score for this sequence is 8 / 15.

II. Overview of Coh-Matrix 3.0 Indices

This Appendix provides the list of indices in Coh-Matrix Version 3.0. The first column provides the label that appears in the output in the current version. The second column provides the label used in prior versions of Coh-Matrix. The third column provides a short description of the index.

Table 1: Indices in the Coh-Matrix 3.0 Output File

Title			Title
Genre			Genre
Source			Source
UserCode			UserCode
LSASpace			LSASpace
Date			Date
Time			Time
	Label in Version 3.x	Label in Version 2.x	Description
Descriptive			
1	DESPC	READNP	Paragraph count, number of paragraphs
2	DESSC	READNS	Sentence count, number of sentences
3	DESWC	READNW	Word count, number of words
4	DESPL	READAPL	Paragraph length, number of sentences, mean
5	DESPLd	n/a	Paragraph length, number of sentences, standard deviation
6	DESSL	READASL	Sentence length, number of words, mean
7	DESSLd	n/a	Sentence length, number of words, standard deviation
8	DESWLsy	READASW	Word length, number of syllables, mean
9	DESWLsyd	n/a	Word length, number of syllables, standard deviation
10	DESWLit	n/a	Word length, number of letters, mean
11	DESWLitd	n/a	Word length, number of letters, standard deviation
Text Easability Principal Component Scores			
12	PCNARz	n/a	Text Easability PC Narrativity, z score
13	PCNARp	n/a	Text Easability PC Narrativity, percentile
14	PCSYNz	n/a	Text Easability PC Syntactic simplicity, z score
15	PCSYNp	n/a	Text Easability PC Syntactic simplicity, percentile
16	PCCNCz	n/a	Text Easability PC Word concreteness, z score
17	PCCNCp	n/a	Text Easability PC Word concreteness, percentile
18	PCREFz	n/a	Text Easability PC Referential cohesion, z score
19	PCREFp	n/a	Text Easability PC Referential cohesion, percentile
20	PCDCz	n/a	Text Easability PC Deep cohesion, z score
21	PCDCp	n/a	Text Easability PC Deep cohesion, percentile
22	PCVERBz	n/a	Text Easability PC Verb cohesion, z score
23	PCVERBp	n/a	Text Easability PC Verb cohesion, percentile
24	PCCONNZ	n/a	Text Easability PC Connectivity, z score
25	PCCONNp	n/a	Text Easability PC Connectivity, percentile
26	PCTEMPz	n/a	Text Easability PC Temporality, z score
27	PCTEMPp	n/a	Text Easability PC Temporality, percentile
Referential Cohesion			
28	CRFNO1	CRFBN1um	Noun overlap, adjacent sentences, binary, mean
29	CRFAO1	CRFBA1um	Argument overlap, adjacent sentences, binary, mean
30	CRFSO1	CRFBS1um	Stem overlap, adjacent sentences, binary, mean
31	CRFNOa	CRFBNaum	Noun overlap, all sentences, binary, mean
32	CRFAOa	CRFBAaum	Argument overlap, all sentences, binary, mean
33	CRFSOa	CRFBSaum	Stem overlap, all sentences, binary, mean
34	CRFCWO1	CRFPC1um	Content word overlap, adjacent sentences, proportional, mean

35	CRFCWO1d	n/a	Content word overlap, adjacent sentences, proportional, standard deviation
36	CRFCWOa	CRFPCaum	Content word overlap, all sentences, proportional, mean
37	CRFCWOad	n/a	Content word overlap, all sentences, proportional, standard deviation
38	CRFANP1	CREFP1u	Anaphor overlap, adjacent sentences
39	CRFANPa	CREFPau	Anaphor overlap, all sentences
LSA			
40	LSASS1	LSAassa	LSA overlap, adjacent sentences, mean
41	LSASS1d	LSAassd	LSA overlap, adjacent sentences, standard deviation
42	LSASSp	LSApssa	LSA overlap, all sentences in paragraph, mean
43	LSASSpd	LSApssd	LSA overlap, all sentences in paragraph, standard deviation
44	LSAPP1	LSAppa	LSA overlap, adjacent paragraphs, mean
45	LSAPP1d	LSAppd	LSA overlap, adjacent paragraphs, standard deviation
46	LSAGN	LSAGN	LSA given/new, sentences, mean
47	LSAGNd	n/a	LSA given/new, sentences, standard deviation
Lexical Diversity			
48	LDTRc	TYPTOKc	Lexical diversity, type-token ratio, content word lemmas
49	LDTRa	n/a	Lexical diversity, type-token ratio, all words
50	LDMTLDa	LEXDIVTD	Lexical diversity, MTLTLD, all words
51	LDVOCda	LEXDIVVD	Lexical diversity, VOCd, all words
Connectives			
52	CNCAI	CONi	All connectives incidence
53	CNCCaus	CONCAUSi	Causal connectives incidence
54	CNCLogic	CONLOGi	Logical connectives incidence
55	CNCADC	CONADVCONi	Adversative and contrastive connectives incidence
56	CNCTemp	CONTEMPI	Temporal connectives incidence
57	CNCTempx	CONTEMPEXi	Expanded temporal connectives incidence
58	CNCAAdd	CONADDi	Additive connectives incidence
59	CNCPos	n/a	Positive connectives incidence
60	CNCCNeg	n/a	Negative connectives incidence
Situation Model			
61	SMCAUSv	CAUSV	Causal verb incidence
62	SMCAUSvp	CAUSVP	Causal verbs and causal particles incidence
63	SMINTEp	INTEi	Intentional verbs incidence
64	SMCAUSr	CAUSC	Ratio of casual particles to causal verbs
65	SMINTEr	INTEC	Ratio of intentional particles to intentional verbs
66	SMCAUSlsa	CAUSLSA	LSA verb overlap
67	SMCAUSwn	CAUSWN	WordNet verb overlap
68	SMTEMP	TEMPta	Temporal cohesion, tense and aspect repetition, mean
Syntactic Complexity			
69	SYNLE	SYNLE	Left embeddedness, words before main verb, mean
70	SYNNP	SYNNP	Number of modifiers per noun phrase, mean
71	SYNMEDpos	MEDwtm	Minimal Edit Distance, part of speech
72	SYNMEDwrd	MEDawm	Minimal Edit Distance, all words
73	SYNMEDlem	MEDalm	Minimal Edit Distance, lemmas
74	SYNSTRUTa	STRUTa	Sentence syntax similarity, adjacent sentences, mean.
75	SYNSTRUTt	STRUTt	Sentence syntax similarity, all combinations, across paragraphs, mean
Syntactic Pattern Density			
76	DRNP	n/a	Noun phrase density, incidence
77	DRVp	n/a	Verb phrase density, incidence
78	DRAP	n/a	Adverbial phrase density, incidence
79	DRPP	n/a	Preposition phrase density, incidence
80	DRPVAL	AGLSPSVi	Agentless passive voice density, incidence
81	DRNEG	DENNEGi	Negation density, incidence
82	DRGERUND	GERUNDi	Gerund density, incidence
83	DRINF	INFi	Infinitive density, incidence
Word Information			
84	WRDNOUN	NOUNi	Noun incidence
85	WRDVERB	VERBi	Verb incidence
86	WRDADJ	ADJi	Adjective incidence
87	WRDADV	ADVi	Adverb incidence
88	WRDPRP	DENPRPi	Pronoun incidence
89	WRDPRP1s	n/a	First person singular pronoun incidence
90	WRDPRP1p	n/a	First person plural pronoun incidence

91	WRDPRP2	PRO2i	Second person pronoun incidence
92	WRDPRP3s	n/a	Third person singular pronoun incidence
93	WRDPRP3p	n/a	Third person plural pronoun incidence
94	WRDPRQc	FRCLacwm	CELEX word frequency for content words, mean
95	WRDPRQa	FRCLaewm	CELEX Log frequency for all words, mean
96	WRDPRQmc	FRCLmcs m	CELEX Log minimum frequency for content words, mean
97	WRDAQAc	WRDAacwm	Age of acquisition for content words, mean
98	WRDFAMc	WRDFacwm	Familiarity for content words, mean
99	WRDCNCc	WRDCacwm	Concreteness for content words, mean
100	WRDIMGc	WRDIacwm	Imagability for content words, mean
101	WRDMEAc	WRDMacwm	Meaningfulness, Colorado norms, content words, mean
102	WRDPOLc	POLm	Polysemy for content words, mean
103	WRDHYPn	HYNOUNaw	Hypernymy for nouns, mean
104	WRDHYPv	HYVERBaw	Hypernymy for verbs, mean
105	WRDHYPnv	HYPm	Hypernymy for nouns and verbs, mean
Readability			
106	RDFRE	READFRE	Flesch Reading Ease
107	RDFKGL	READFKGL	Flesch-Kincaid Grade Level
108	RDL2	L2	Coh-Metrix L2 Readability

III. Indices in the Coh-Metrix 3.0 output file



The indices in Coh-Metrix 3.0 are categorized into eleven groups: (1) Descriptive, (2) Text Easability Principal Component Scores, (3) Referential Cohesion, (4) LSA, (5) Lexical Diversity, (6) Connectives, (7) Situation Model, (8) Syntactic Complexity, (9) Syntactic Pattern Density, (10) Word Information, and (11) Readability.

1. Descriptive Indices

Coh-Metrix provides descriptive indices to help the user to check the Coh-Metrix output (e.g., to make sure that the numbers make sense) and also to interpret patterns of data. The extracted indices include those listed below. In the output for the current version of Coh-Metrix (Version 3.0) all of these indices are preceded by DES to designate that they are *descriptive* measures.

Number of paragraphs (DESPC). (index 01)

This is the total number of paragraphs in the text. Paragraphs are simply delimited by a hard return.

Number of sentences (DESSC). (index 02)

This is the total number of sentences in the text. Sentences are identified by the OpenNLP sentence splitter (<http://opennlp.sourceforge.net/projects.html>).

Number of words (DESWC). (index 03)

This is the total number of words in the text. Words are calculated using the output from the Charniak parser. For each sentence, the Charniak parser generates a parse tree with part of speech (POS) tags for clauses, phrases, words and punctuations. The elements on the leaves of a parse tree are tagged words or punctuations. In Coh-Metrix, words are taken from the leaves of the sentence parse trees.

Mean length of paragraphs (DESPL). (index 04)

This is the average number of sentences in each paragraph within the text. Longer paragraphs may be more difficult to process.

Standard deviation of the mean length of paragraphs (DESPLd). (index 05)

This is the standard deviation of the measure for the mean length of paragraphs within the text. In the output, *d* is used at the end of the name of the indices to designate that it is a standard deviation. A large standard deviation indicates that the text has large variation in terms of the lengths of its paragraphs, such that it may have some very short and some very long paragraphs. The presence of headers in a short text can increase values on this measure.

Mean number of words (length) of sentences in (DESSL). (index 06)

This is the average number of words in each sentence within the text, where a word is anything that is tagged as a part-of-speech by the Charniak parser. Sentences with more words may have more complex syntax and may be more difficult to process. While this is a descriptive measure, this also provides one commonly used proxy for syntactic complexity. However, Coh-Metrix provides additional more precise measures of syntactic complexity discussed later in this chapter.

Standard deviation of the mean length of sentences (DESSLd). (index 07)

This is the standard deviation of the measure for the mean length of sentences within the text. A large standard deviation indicates that the text has large variation in terms of the lengths of its sentences, such that it may have some very short and some very long sentences. The presence of headers in a short text may impact this measure. Narrative text may also have variations in sentence length as authors move from short character utterances to long descriptions of scenes.

Mean number of syllables (length) in words (DESWLsy). (index 08)

Coh-Metrix calculates the average number of syllables in all of the words in the text. Shorter words are easier to read and the estimate of word length serves as a common proxy for word frequency.

Standard deviation of the mean number of syllables in words (DESWLsyd). (index 09)

This is the standard deviation of the measure for the mean number of syllables in the words within the text. A large standard deviation indicates that the text has large variation in terms of the lengths of its words, such that it may have both short and long words.

Mean number of letters (length) in words (DESWLit). (index 10)

This is the average number of letters for all of the words in the text. Longer words tend to be lower in frequency or familiarity to a reader.

Standard deviation of the mean number of letter in words (DESWLtd). (index 11)

This is the standard deviation of the measure for the mean number of letters in the words within the text. A large standard deviation indicates that the text has large variation in terms of the lengths of its words, such that it may have both short and long words.

2. Text Easability Principal Component Scores

Recent work has culminated in the development of the Coh-Metrix *Easability* components (Graesser, McNamara, & Kulikowich, 2011). These components provide a more complete picture of text ease (and difficulty) that emerge from the linguistic characteristics of texts. The Easability components provided by Coh-Metrix go beyond traditional readability measures by providing metrics of text characteristics on multiple levels of language and discourse. Moreover, they are well-aligned with theories of text and discourse comprehension (e.g., Graesser, Singer, & Trabasso, 1994; Graesser & McNamara, 2011; Kintsch, 1998; McNamara & Magliano, 2009).

Narrativity: PCNARz, PCNARp (index 12, 13)

Narrative text tells a story, with characters, events, places, and things that are familiar to the reader. Narrative is closely affiliated with everyday, oral conversation. This robust component is highly affiliated with word familiarity, world knowledge, and oral language. Non-narrative texts on less familiar topics lie at the opposite end of the continuum.

Syntactic Simplicity: PCSYNz, PCSYNp (index 14, 15)

This component reflects the degree to which the sentences in the text contain fewer words and use simpler, familiar syntactic structures, which are less challenging to process. At the opposite end of the continuum are texts that contain sentences with more words and use complex, unfamiliar syntactic structures.

Word Concreteness: PCCNCz, PCCNCp (index 16, 17)

Texts that contain content words that are concrete, meaningful, and evoke mental images are easier to process and understand. Abstract words represent concepts that are difficult to represent visually. Texts that contain more abstract words are more challenging to understand.

Referential Cohesion: PCREFz, PCREFp (index 18, 19)

A text with high referential cohesion contains words and ideas that overlap across sentences and the entire text, forming explicit threads that connect the text for the reader. Low cohesion text is typically more difficult to process because there are fewer connections that tie the ideas together for the reader.

Deep Cohesion: PCDCz, PCDCp (index 20, 21)

This dimension reflects the degree to which the text contains causal and intentional connectives when there are causal and logical relationships within the text. These connectives help the reader to form a more coherent and deeper understanding of the causal events, processes, and actions in the text. When a text contains many relationships but does not contain those connectives, then the reader must infer the relationships between the ideas in the text. If the text is high in deep cohesion, then those relationships and global cohesion are more explicit.

Verb Cohesion: PCVERBz, PCVERBp (index 22, 23)

This component reflects the degree to which there are overlapping verbs in the text. When there are repeated verbs, the text likely includes a more coherent event structure that will facilitate and enhance situation model understanding. This component score is likely to be more relevant for texts intended for younger readers and for narrative texts (McNamara, Graesser, & Louwerse, 2012).

Connectivity: PCCONNz, PCCONNp (index 24, 25)

This component reflects the degree to which the text contains explicit adversative, additive, and comparative connectives to express relations in the text. This component reflects the number of logical relations in the text that are explicitly conveyed. This score is likely to be related to the reader's deeper understanding of the relations in the text.

Temporality: PCTEMPz, PCTEMPp (index 26, 27)

Texts that contain more cues about temporality and that have more consistent temporality (i.e., tense, aspect) are easier to process and understand. In addition, temporal cohesion contributes to the reader's situation model level understanding of the events in the text.

3. Referential Cohesion

Referential cohesion refers to overlap in content words between local sentences, or *co-reference*. In the output for the current version of Coh-Metrix (Version 3.0), all of these indices are preceded by CRF to designate that they are *co-reference* measures. Co-reference is a linguistic cue that can aid readers in making connections between propositions, clauses, and sentences in their textbase understanding (Halliday & Hasan, 1976; McNamara & Kintsch, 1996). Coh-Metrix measures for referential cohesion vary along two dimensions. First, the indices vary from local to more global. Local cohesion is measured by assessing the overlap between consecutive, adjacent sentences, whereas global cohesion is assessed by measuring the overlap between all of the sentences in a paragraph or text. Additional information about the co-reference measures are provided below.

Noun overlap (CRFNO1 and CRFNOa). (index 28, 31)

These are measures of local and global overlap between sentences in terms of nouns. Adjacent noun overlap (CRFNO1) represents the average number of sentences in the text that have noun overlap from one sentence back to the previous sentence. Among the co-reference measures, it is the most strict, in the sense that the noun must match exactly, in form and plurality.

Whereas local overlap considers only adjacent sentences, global overlap (CRFNOa) considers the overlap of each sentence with every other sentence. As shown in Table 4.1, just over 50 percent of the adjacent sentences contained an overlapping noun, and 43 percent of the sentence pairs in the text contained an overlapping noun when comparing all of the sentences (global overlap).

Argument overlap (CRFAO1 and CRFAOa). (index 29, 32)

These local and global overlap measures are similar to noun overlap measures, but include overlap between sentences in terms of nouns and pronouns. Argument overlap occurs when there is overlap between a noun in one sentence and the same noun (in singular or plural form) in another sentence; it also occurs when there are matching personal pronouns between two sentences (e.g., he/he). The term argument is used in a linguistic sense, where noun/pronoun arguments are contrasted with verb/adjective predicates (Kintsch & Van Dijk, 1978). Consider argument overlap for the science passage in Table 4.1 in the second column. Note that in comparison to noun overlap, it is less strict because it considers the overlap for example between *cells* and *cell*. Argument and stem overlap would also include overlap between pronouns, such as *it* to *it*, or *he* to *he*, which noun overlap does not include.

Stem overlap (CRFSO1, CRFSOa). (index 30, 33)

These two local and global overlap measures relax the noun constraint held by the noun and argument overlap measures. A noun in one sentence is matched with a content word (i.e., nouns, verbs, adjectives, adverbs) in a previous sentence that shares a common lemma (e.g., tree/treed; mouse/mousey; price/priced). Notably, the outcome for stem and argument overlap in Table 4.1 were identical; however, this will not always be the case.

Content word overlap (CRFCWO1, CRFCWO1d, CRFCWOa, CRFCWOad) . (index 34, 35, 36, 37)

This measure considers the proportion of explicit content words that overlap between pairs of sentences. For example, if a sentence pair has fewer words and two words overlap, the proportion is greater than if a pair has many words and two words overlap. This measure includes both local (CRFCWO1) and global (CRFCWOa) indices, and also includes their standard deviations (CRFCWO1d, CRFCWOad). In the example provided in Table 4.1, the content word overlap both locally and globally was lower than that estimated by the binary overlap scores. This measure may be particularly useful when the lengths of the sentences in the text are a principal concern.

Anaphor overlap (CRFANP1, CRFANPa) (index 38,39)

This measure considers the anaphor overlap between pairs of sentences. A pair of sentences has an anaphor overlap if the later sentence contains a pronoun that refers to a pronoun or noun in the earlier sentence. The score for each pair of sentences is binary, i.e., 0 or 1. The measure of the text is the average of the pair scores. This measure includes both local (CRFANP1) and global (CRFANPa) indice.

4. Latent Semantic Analysis

Latent Semantic Analysis (LSA; Landauer et al., 2007) provides measures of semantic overlap between sentences or between paragraphs. Coh-Metrix 3.0 provides eight LSA indices. Each of these measures varies from 0 (low cohesion) to 1 (high cohesion).

LSA sentence adjacent: LSASS1(index 40)

This index computes mean LSA cosines for adjacent, sentence-to-sentence (abbreviated as "ass") units. This measures how conceptually similar each sentence is to the next sentence.

Example:

Text 1: The field was full of lush, green grass. The horses grazed peacefully. The young children played with kites. The women occasionally looked up, but only occasionally. A warm summer breeze blew and everyone, for once, was almost happy.

Text 2: The field was full of lush, green grass. An elephant is a large animal. No-one appreciates being lied to. What are we going to have for dinner tonight?

In the example texts printed above, Text 1 records much higher LSA scores than Text 2. The words in Text 1 tend to be thematically related to a pleasant day in an idyllic park scene: *green, grass, children, playing, summer, breeze, kites, and happy*. In contrast, the sentences in Text 2 tend to be unrelated.

LSASS1d (index 41)

This index computes standard deviation of LSA cosines for adjacent, sentence-to-sentence (abbreviated as "ass") units. This measures how consistent adjacent sentences are overlapped semantically.

LSA sentence all: LSASSp (index 42)

Like LSA sentence adjacent (LSAassa), this index computes mean LSA cosines. However, for this index all sentence combinations are considered, not just adjacent sentences. LSApssa computes how conceptually similar each sentence is to every other sentence in the text.

LSASSpd (index 43)

This index computes the standard deviation of LSA cosine of all sentence pairs within paragraphs.

LSAPP1 (index 44)

This index computes the mean of the LSA cosines between adjacent paragraphs.

LSAPP1d (index 45)

This index is the standard deviation of LSA cosines between adjacent paragraphs.

LSAGN (index 46)

This is the average givenness of each sentence.

LSAGNd (index 47)

This is the standard deviation of givenness of each sentence.

5. Lexical Diversity

Lexical diversity refers to the variety of unique words (*types*) that occur in a text in relation to the total number of words (*tokens*). When the number of word types is equal to the total number of words (tokens), then all of the words are different. In that case, lexical diversity is at a maximum, and the text is likely to be either very low in cohesion or very short. A high number of different words in a text indicates that new words need to be integrated into the discourse context. By contrast, lexical diversity is lower (and cohesion is higher) when more words are used multiple times across the text.

Type-token ratio: LDTTRc (index 48)

Type-token ratio (TTR) (Templin, 1957) is the number of unique words (called types) divided by the number of tokens of these words. Each unique word in a text is considered a word type. Each instance of a particular word is a token. For example, if the word *dog* appears in the text 7 times, its type value is 1, whereas its token value is 7. When the type-token ratio approaches 1, each word occurs only once in the text; comprehension should be comparatively difficult because many unique words need to be decoded and integrated with the discourse context. **As the type-token ratio decreases, words are repeated many times in the text**, which should increase the ease and speed of text processing. Type-token ratios are computed for content words, but not function words. **TTR scores are most valuable when texts of similar lengths are compared**.

Example:

Cytokinesis, the second stage of cell division, begins to occur before mitosis is complete (usually during telophase) and continues after the nuclei of the daughter cells are completely formed. The preliminary steps of cytokinesis occur during the growth interphases (called the G phases) of the cell cycle.

In these sentences (taken from the text reprinted later in the help facility), the TTR for content words is 0.933. Words such as *stage* only occur once, but words like *cytokinesis* and *cell* appear more than once. Coh-Metrix uses lexeme versions in its calculation rather than lemma or stem versions; for example, *cell* is considered different from *cells*.

LDTTRa (index 49)

Type token ratio for all words.

LDMTLDa (index 50)

MTLD lexical diversity measure for all words.

LDVOCa (index 51)

VOC lexical diversity measure for all words.

6. Connectives

Connectives play an important role in the creation of cohesive links between ideas and clauses and provide clues about text organization (Cain & Nash, 2011; Crismore, Markkanen, & Steffensen, 1993; Longo, 1994; Sanders & Noordman, 2000; van de Kopple, 1985). Coh-Metrix provides an incidence score (occurrence per 1000 words) for all connectives (CNCAI) as well as different types of connectives. Indices are provided on five general classes of connectives (Halliday & Hasan, 1976; Louwerse, 2001): causal (CNCCaus; *because, so*), logical (CNCLogic; *and, or*), adversative/contrastive (CNCADC; *although, whereas*), temporal (CNCTemp; *first, until*), and additive (CNCAAdd; *and, moreover*). In addition, there is a distinction between positive connectives (CNCPos; *also, moreover*) and negative connectives (CNCNeg; *however, but*).

All connectives: CNCAI (index 52)

This is the incidence of all connectives.

Causal Connectives: CNCCaus (index 53)

This is the incidence score of causal connectives. Among the various types of connectives, only causal connectives (CNCCaus) discriminated between the high and low cohesion texts, presumably because the researchers who created the texts primarily manipulated causal cohesion and not additive, temporal, or clarification connectives.

CNCLogic (index 54)

This is the incidence score of logic connectives.

CNCADC (index 55)

This is the incidence score of adversative/contrastive connectives.

CNCTemp (index 56)

This is the incidence score of temporal connectives.

CNCTempx (index 57)

This is the incidence score of extended temporal connectives.

CNCAAdd (index 58)

This is the incidence score of additive connectives.

CNCPos (index 59)

This is the incidence score of positive connectives.

CNCNeg (index 60)

This is the incidence score of negative connectives.

7. Situation Model

The expression *situation model* has been used by researchers in discourse processing and cognitive science to refer to the level of mental representation for a text that involves much more than the explicit words (van Dijk & Kintsch, 1983; Graesser & McNamara,

2011; Graesser, Singer, & Trabasso, 1994; Kintsch, 1998; Zwaan & Radvansky, 1998). Some researchers have described the situational model in terms of the features that are present in the comprehender's mental representation when a given context is activated (e.g., Singer & Leon, 2007). For example, with episodes in narrative text, the situation model would include *the plot*. In an informational text about the circulatory system, the situation model might convey *the flow of the blood*.

SMCAUSv (index 61)

This is the incidence score of causal verbs.

Causal content: SMCAUSvp (index 62)

This is the incidence of causal verbs and causal particles in text.

Intentional content: SMINTEp (index 63)

This is the incidence of intentional actions, events, and particles (per thousand words).

Causal cohesion: SMCAUSr (index 64)

This is a ratio of causal particles (P) to causal verbs (V). The denominator is incremented by the value of 1 to handle the rare case when there are 0 causal verbs in the text. Cohesion suffers when the text has many causal verbs (signifying events and actions) but few causal particles that signal how the events and actions are connected.

To see the list of causal particles [click here](#)

Intentional cohesion: SMINTER (index 65)

This is the ratio of intentional particles to intentional actions/events.

SMCAUSlsa (index 66)

This is the LSA overlap between verbs.

SMCAUSwn (index 67)

This is the WordNet overlap between verbs.

Temporal cohesion: SMTEMP (index 68)

This is the repetition score for tense and aspect. The repetition score for tense is averaged with the repetition score for aspect.

8. Syntactic Complexity

Theories of syntax assign words to part-of-speech categories (e.g., nouns, verbs, adjectives, conjunctions), group words into phrases or constituents (noun-phrases, verb-phrases, prepositional-phrases, clauses), and **construct syntactic tree structures for sentences**. For example, some sentences are short and have a simple syntax that follow an actor-action-object syntactic pattern, have few if any embedded clauses, and have an active rather than passive voice. Some sentences have complex, embedded syntax that potentially places heavier demands on working memory. The syntax in text tends to be easier to process when there are shorter sentences, few words before the main verb of the main clause, and few words per noun-phase.

Words before main verb: SYNLE (index 69)

This is the mean number of words before the main verb of the main clause in sentences. **This is a good index of working memory load.**

Modifiers per NP: SYNNP (index 70)

This is the mean number of modifiers per noun-phrase.

SYNMEDpos (index 71)

This is the mean minimum editorial distance score between adjacent sentences computed from part of speech tags. Notice that the editing actions were performed on POS tags in two sentences instead of letters in two words. See Coh-Metrix book for details.

SYNMEDwrd (index 72)

This is the minimum editorial distance score between adjacent sentences computed from words. Notice that the editing actions were performed on words in two sentences instead of letters in two words. See Coh-Metrix book for details.

SYNMEDlem (index 73)

This is the minimum editorial distance score between adjacent sentences from lemmas. Notice that the editing actions were performed on lemmas in two sentences instead of letters in two words. See Coh-Metrix book for details.

Syntactic structure similarity adjacent: SYNSTRUTa (index 74)

This is the proportion of intersection tree nodes between all adjacent sentences.

Syntactic structure similarity all 01: SYNSTRUTt (index 75)

This is the proportion of intersection tree nodes between all sentences and across paragraphs.

9. Syntactic Pattern Density

Syntactic complexity is also informed by the density of particular syntactic patterns, word types, and phrase types. Coh-Metrix provides information on the incidence of noun phrases (DRNP, verb phrases (DRVP), adverbial phrases (DRAP), and prepositions (DRPP). The relative density of each of these can be expected to affect processing difficulty of text, particularly with respect to other features in a text. For example, if a text has a higher noun and verb phrase incidence, it is more likely to be informationally dense with complex syntax.

DRNP (index 76)

This is the incidence score of noun phrases.

DRVP (index 77)

This is the incidence score of verb phrases.

DRAP (index 78)

This is the incidence score of adverbial phrases.

DRPP (index 79)

This is the incidence score of preposition phrases.

DRPVAL (index 80)

This is the incidence score of agentless passive voice forms.

Negations: DRNEG (index 81)

This is the incidence score for negation expressions.

DRGERUND (index 82)

This is the incidence score of gerunds.

DRINF (index 83)

This is the incidence score of infinitives.

10. Word Information

Word information refers to the idea that each word is assigned a syntactic part-of-speech category thus, syntactic categories are segregated into content words (e.g., nouns, verbs, adjectives, adverbs) and function words (e.g., prepositions, determiners, pronouns). Many words can be assigned to multiple syntactic categories. For example, the word "bank" can be a noun ("river bank"), a verb ("don't bank on it"), or an adjective ("bank shot"). Coh-Metrix assigns only one part-of-speech category to each word on the basis of its syntactic context. In addition, Coh-Metrix computes word frequency scores and psychological ratings.

WRDNOUN (index 84)

This is the incidence score of nouns.

WRDVERB (index 85)

This is the incidence score of verbs.

WRDADJ (index 86)

This is the incidence score of adjectives.

WRDADV (index 87)

This is the incidence score of adverbs.

Personal pronoun: WRDPRO (index 88)

This is the number of personal pronouns per 1000 words. A high density of pronouns can create referential cohesion problems if the reader does not know what the pronouns refer to.

Example:

Paul told John that he wanted to help him out.

The words *he* and *him* in this sentence are both pronouns, leading to a density score of 200. The pronouns, however, are ambiguous as we do not know which pronoun refers to which person.

WRDPRP1s (index 89)

This is the incidence score of pronouns, first person, single form.

WRDPRP1p (index 90)

This is the incidence score of pronouns, first person, plural form.

WRDPRP2 (index 91)

This is the incidence score of pronouns, second person.

WRDPRP3s (index 92)

This is the incidence score of pronouns, third person, single form.

WRDPRP3p (index 93)

This is the incidence score of pronouns, third person, plural form.

WRDFRQc (index 94)

This is the average word frequency for content words.

WRDFRQa (index 95)

This is the average word frequency for all words.

WRDFRQmc (index 96)

This is the average minimum word frequency in sentences.

Age of acquisition (WRDAOAc). (index 97)

Coh-Metrix includes the age of acquisition norms from MRC which were compiled by Gilhooly and Logie (1980) for 1903 unique words. The *c* at the end of the index name indicates that it is calculated for the average ratings for content words in a text. Age of acquisition reflects the notion that some words appear in children's language earlier than others. Words such as *cortex*, *dogma*, and *matrix* (AOA=700) have higher age-of-acquisition scores than words such as *milk*, *smile*, and *pony* (AOA=202). Words with higher age-of-acquisition scores denote spoken words that are learned later by children.

Familiarity (WRDFAMc). (index 98)

This is a rating of how familiar a word seems to an adult. Sentences with more familiar words are words that are processed more quickly. MRC provides ratings for 3488 unique words. Coh-Metrix provides the average ratings for content words in a text. Raters for

familiarity provided ratings using a 7-point scale, with 1 being assigned to words that they never had seen and 7 to words that they had seen very often (nearly every day). The ratings were multiplied by 100 and rounded to integers.

For example, the words *milk* (588), *smile* (594), and *pony* (524) have an average Familiarity of 569 compared to the words *cornet* (364), *dogma* (328), and *manus* (113), which have an average Familiarity of 268. Words with very high Familiarity include *mother* (632) and *water* (641), compared to *calix* (124) and *witan* (110).

Concreteness (WRDCNCc). (index 99)

This is an index of how concrete or non-abstract a word is. Words that are more concrete are those things you can hear, taste, or touch. MRC provides ratings for 4293 unique words. Coh-Metrix provides the average ratings for content words in a text. Words that score low on the concreteness scale include *protocol* (264) and *difference* (270) compared to *box* (597) and *ball* (615).

Imagability (WRDIMGc). (index 100)

An index of how easy it is to construct a mental image of the word is also provided in the merged ratings of the MRC, which provides ratings for 4825 words. Coh-Metrix provides the average ratings for content words in a text. Examples of low imagery words are *reason* (285), *dogma* (327), and *overtone* (268) compared to words with high imagery such as *bracelet* (606) and *hammer* (618).

Meaningfulness (WRDMEAc). (index 101)

These are the meaningfulness ratings from a corpus developed in Colorado by Toglia and Battig (1978). MRC provides ratings for 2627 words. Coh-Metrix provides the average ratings for content words in a text. An example of meaningful word is *people* (612) as compared to *abbess* (218). Words with higher meaningfulness scores are highly associated with other words (e.g., *people*), whereas a low meaningfulness score indicates that the word is weakly associated with other words.

Polysemy (WRDPOLc). (index 102)

Polysemy refers to the number of senses (core meanings) of a word. For example, the word *bank* has at least two senses, one referring to a building or institution for depositing money and the other referring to the side of a river. Coh-Metrix provides average polysemy for content words in a text. Polysemy relations in WordNet are based on synsets (i.e., groups of related lexical items), which are used to represent similar concepts but distinguish between synonyms and word senses (Miller et al., 1990). These synsets allow for the differentiation of senses and provide a basis for examining the number of senses associated with a word. Coh-Metrix reports the mean WordNet polysemy values for all content words in a text. Word polysemy is considered to be indicative of text ambiguity because the more senses a word contains relates to the potential for a greater number of lexical interpretations. However, more frequent words also tend to have more meanings, and so higher values of polysemy in a text may be reflective of the presence of higher frequency words.

Hypernymy (WRDHYPn, WRDHYPv, WRDHYPnv). (index 103, 104, 105)

Coh-Metrix also uses WordNet to report word hypernymy (i.e., word specificity). In WordNet, each word is located on a hierarchical scale allowing for the measurement of the number of subordinate words below and superordinate words above the target word. Thus, *entity*, as a possible hypernym for the noun *chair*, would be assigned the number 1. All other possible hyponyms of entity as it relates to the concept of a chair (e.g., *object*, *furniture*, *seat*, *chair*, *camp chair*, *folding chair*) would receive higher values (see also Chapter 2). Similar values are assigned for verbs (e.g., *hightail*, *run*, *travel*). As a result, a lower value reflects an overall use of less specific words, while a higher value reflects an overall use of more specific words. Coh-Metrix provides estimates of hypernymy for nouns (WRDHYPn), verbs (WRDHYPv), and a combination of both nouns and verbs (WRDHYPnv).

11. Readability

The traditional method of assessing texts on difficulty consists of various readability formulas. More than 40 readability formulas have been developed over the years (Klare, 1974-1975). The most common formulas are the Flesch Reading Ease Score and the Flesch Kincaid Grade Level.

Flesch Reading Ease: RDFRE (index 106)

The output of the Flesch Reading Ease formula is a number from 0 to 100, with a higher score indicating easier reading. The average document has a Flesch Reading Ease score between 6 and 70. The formula is provided below:

$$\text{READFRE} = 206.835 - (1.015 \times \text{ASL}) - (84.6 \times \text{ASW})$$

where:

ASL = average sentence length = the number of words divided by the number of sentences. This is the same as READASL.

ASW (comes from CELEX database) = average number of syllables per word = the number of syllables divided by the number of words. This is the same as READASW.

Flesch_Kincaid Grade Level: RDFKGL (index 107)

This more common Flesch-Kincaid Grade Level formula converts the Reading Ease Score to a U.S. grade-school level. The higher the number, the harder it is to read the text. The grade levels range from 0 to 12.

$$\text{READFKGL} = (.39 \times \text{ASL}) + (11.8 \times \text{ASW}) - 15.59$$

In general, a text should generally have more than 200 words before the Flesch Reading Ease and Flesch-Kincaid Grade Level scores can successfully be applied.

RDL2 (index 108)

This is the second language readability score.

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V. Example Text and Output

[Example Text](#)

Coh-Metrix Output for Example Text

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