

See discussions, stats, and author profiles for this publication at: <https://www.researchgate.net/publication/370817632>

# CohExplore: Visually Supporting Students in Exploring Text Cohesion

Preprint · May 2023

---

CITATIONS  
0

---

READS  
42

3 authors:



**Carina Liebers**

University of Duisburg-Essen

8 PUBLICATIONS 19 CITATIONS

SEE PROFILE



**Shivam Agarwal**

Otto-Friedrich-Universität Bamberg

24 PUBLICATIONS 70 CITATIONS

SEE PROFILE



**Fabian Beck**

Otto-Friedrich-Universität Bamberg

118 PUBLICATIONS 2,484 CITATIONS

SEE PROFILE

# CohExplore: Visually Supporting Students in Exploring Text Cohesion

C. Liebers<sup>†1</sup>, S. Agarwal<sup>2</sup>, and F. Beck<sup>2</sup>

<sup>1</sup>University of Duisburg-Essen, Germany

<sup>2</sup>University of Bamberg, Germany

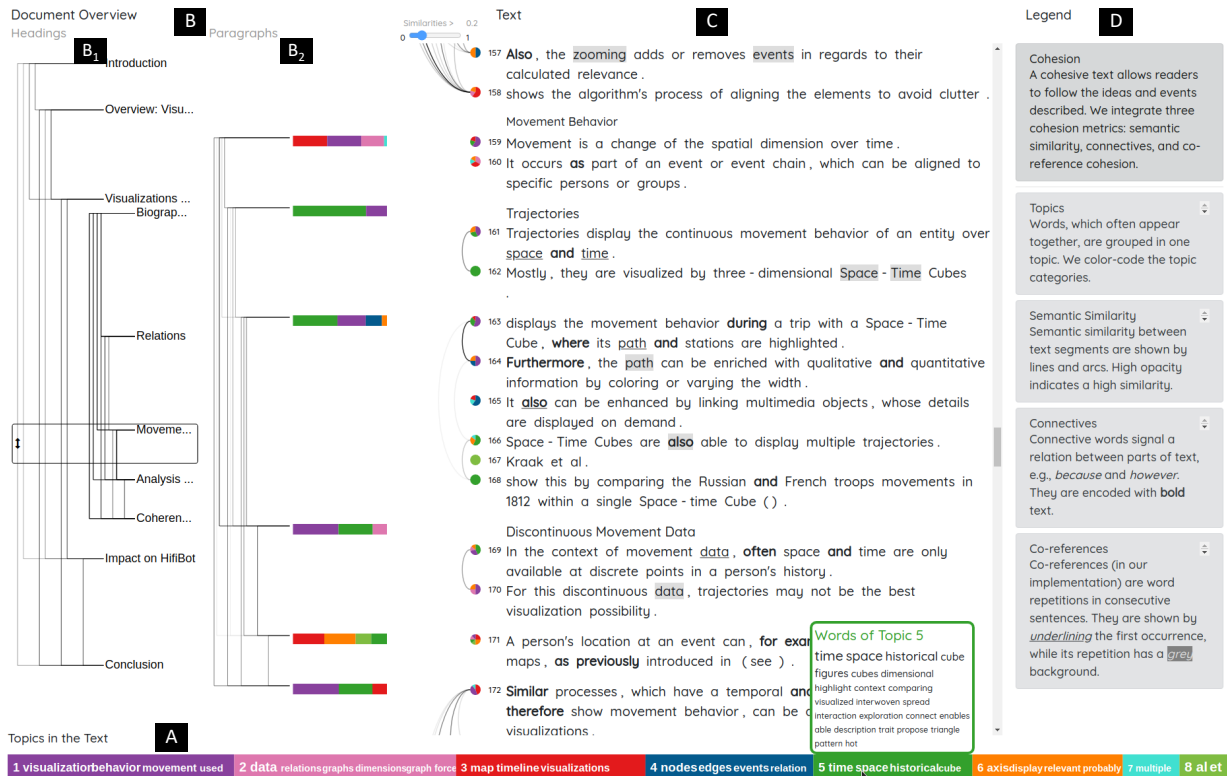


Figure 1: CohExplore shows (A) a colored bar for detected topics, (B) the document structure with similarity lines between (B<sub>1</sub>) the text headings and (B<sub>2</sub>) paragraphs, (C) the raw text with decorations and similarity arcs, and (D) an interactive legend.

## Abstract

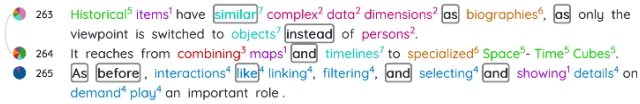
A cohesive text allows readers to follow the described ideas and events. Exploring cohesion in text might aid students enhancing their academic writing. We introduce CohExplore, which promotes exploring and reflecting on cohesion of a given text by visualizing computed cohesion-related metrics on an overview and detailed level. Detected topics are color-coded, semantic similarity is shown via lines, while connectives and co-references in a paragraph are encoded using text decoration. Demonstrating the system, we share insights about a student-authored text.

## 1. Introduction

Students with limited experience and skills in writing face challenges in authoring a text that is easy to follow for the readers—

the text might lack cohesion. Text cohesion is a property of the text that involves features that guide readers in interpreting substantial ideas [GMLC04, GMK11, GM11]. Topics reflect the overall text structure and semantics. Semantic similarity, based on topic detection, is significantly higher for high-cohesion than low-cohesion texts [MLMG10] and can be calculated using Latent Se-

<sup>†</sup> e-mail: carina.liebers@uni-due.de



**Figure 2:** Selecting a paragraph shows the topic words in their respective color. Hovering the connectives tile in the legend highlights connectives through borders.

mantic Analysis (LSA), word2vec, and Latent Dirichlet Allocation (LDA) [CKD19]. *Referential cohesion* [GMLC04], the references between words, contributes on a lower abstraction level. Further, cohesive texts incorporate more *co-references*, where a noun or pronoun refers back to another element in the text [MLMG10]. *Connectives*, such as “because”, “while”, or “however”, improve comprehension of a text by contributing to local cohesion [KPMs19].

## 2. Visualization Approach

We present CohExplore (Fig. 1), an approach that visualizes cohesion-related metrics to aid reflection. It consists of an overview showing similarities of chapters and paragraphs and a reading view. It does not judge the text quality or provide scores but invites exploring text features that contribute to its cohesion. CohExplore aims to support analyzing texts by visualizing: (1) semantic text similarity, (2) connectives, and (3) co-references, covering global (1) and local (2, 3) features of text cohesion.

Regarding global cohesion, we use Latent Semantic Analysis (LSA) [LMDK07, Dos26] with a computed topic number [Nav09] to identify topics in a text by grouping frequently co-occurring words. CohExplore leverages these topics to compute the semantic similarity between text segments: pairs of sentences, paragraphs, and chapters. We compute the cosine similarity of their vectors, containing their impact values per topic. The results range between 0 (lowest) and 1 (highest).

**Topic Bars** The discovered topics are color-coded consistently and displayed at the bottom of the interface as a horizontal stacked bar (Fig. 1A). Their width indicates the topic’s share in the text. Hovering reveals a list of words, ordered by their impact value for their topic. The font size encodes the impact value.

**Document Overview** The *Document Overview* on the left (Fig. 1B) is split into two columns and was inspired by VarifocalReader [KJW\*14]. The *headings* column (Fig. 1B<sub>1</sub>) shows the hierarchical structure of the text via indentation. In the *paragraphs* column (Fig. 1B<sub>2</sub>), colored stacked bars show the topic distribution of paragraphs. Users can scroll or click on headings, or drag a frame to navigate the document. The other columns follow. Additional lines depict semantic similarity among chapters, subchapters, and paragraphs, to support analyzing if similarities are expected or desired, ordered hierarchically to minimize overlap. Their opacity encodes their similarity.

**Text Cohesion in Paragraphs** To show aspects of local cohesion, the *text* panel (Fig. 1C, Fig. 2) highlights cohesion between sentences. Pie charts show topic distribution of sentences to spot

unusual patterns like multiple discussed topics. Arcs depict the semantic similarity within a paragraph, their opacity encodes the similarity value. We chose slightly different visualizations for topic distribution and semantic similarity to visually discern them from the overview, which has more text and topic words. Text decorations display local features: co-references, connectives, and a word’s topic. Co-references, pointing to the previous or following sentence, are detected using word lemmas (stem), and are underlined in the first and given a **grey** background on subsequent occurrences. Commonly used connectives, indicating relations between arguments, are emphasized in **bold** to not interfere with the co-references encoding. When selecting a paragraph, words are colored and marked with superscript numbers of their topic (Fig. 2).

**Legend and Interactions** The *legend* on the right (Fig. 1D) explains cohesion features and visual encodings. Hovering highlights the feature, like emphasizing connectives with borders (Fig. 2). Clicking a bar or a pie chart reveals links connecting the corresponding segment, while hiding unrelated lines and arcs. A slider enables setting a minimal threshold for similarity links.

## 3. Application Example

We explore a seminar report’s cohesion (attached as supplement), written by one of the co-authors two years ago as a student. The Overview Panel (Fig. 1B) shows an imbalanced structure, where only one chapter, *Visualizations of Historical Figures and Events*, exhibits subchapters, contributing to over half of the text. Although it contains the report’s main parts, its subchapters show an imbalance of similarity lines. Analyzing the high similarity of *Movement Behavior* and *Analysis of Historical Items*, we observe common themes in topic one ■ and five ■. Their word clouds of the topic bar (Fig. 1A) indicate overlap of *visualization techniques*, *temporal dimension*, and *space-time cubes*. Hence, re-thinking the structure could be promising. Further, the *Conclusion* section might be sub-optimal: While its paragraphs exhibit similarity, the sentence similarity varies a lot. For instance, only the first two sentences have a similarity of >0.2 in the shown paragraph (Fig. 2), indicating a flow shift of discussed topics. Varying pie chart colors indicate abrupt topic shifts (l. 263 ●, l. 264 ●, and l. 265 ●), and the absence of co-references might make the section harder to follow.

## 4. Conclusion and Future Work

We introduced a visualization approach that enables exploring text cohesion. It uses different cohesion metrics such as semantic similarity, connectives, and co-references. Future work includes adding co-reference cohesion metrics [MLMG10]; incorporating measures such as syntactic complexity, readability, and style word usage in its visualizations [GMLC04]; and applying alternative topic detection methods [ASFS18, BZSA18] to improve the topic quality, reduce their overlap, and refine the visualized text cohesion.

## Acknowledgments

We thank Andrea Horbach and Torsten Zesch for valuable feedback on the approach.

## References

- [ASFS18] ALTSZYLER E., SIGMAN M., FERNÁNDEZ SLEZAK D.: Corpus specificity in LSA and word2vec: The role of out-of-domain documents. In *Proceedings of The Third Workshop on Representation Learning for NLP* (2018), pp. 1–10. doi:10.18653/v1/w18-3001. 2
- [BZSA18] BERNARD J., ZEPPELZAUER M., SEDLMAIR M., AIGNER W.: VIAL: A unified process for visual interactive labeling. *The Visual Computer: International Journal of Computer Graphics* 34, 9 (2018), 1189–1207. doi:10.1007/s00371-018-1500-3. 2
- [CKD19] CROSSLEY S. A., KYLE K., DASCALU M.: The Tool for the Automatic Analysis of Cohesion 2.0: Integrating semantic similarity and text overlap. *Behavior Research Methods* 51, 1 (2019), 14–27. doi:10.3758/s13428-018-1142-4. 2
- [Dos26] DOSHI S.: Latent Semantic Analysis — Deduce the hidden topic from the document, 2020-02-26. Accessed: March 2022. URL: <https://towardsdatascience.com/latent-semantic-analysis-deduce-the-hidden-topic-from-the-document-f360e8c0614b>. 2
- [GM11] GRAESSER A. C., MCNAMARA D. S.: Computational analyses of multilevel discourse comprehension. *Topics in Cognitive Science* 3, 2 (2011), 371–398. doi:10.1111/j.1756-8765.2010.01081.x. 1
- [GMK11] GRAESSER A. C., MCNAMARA D. S., KULIKOWICH J. M.: Coh-Metrix: Providing multilevel analyses of text characteristics. *Educational Researcher* 40, 5 (2011), 223–234. doi:10.3102/0013189X11413260. 1
- [GMLC04] GRAESSER A. C., MCNAMARA D. S., LOUWERSE M. M., CAI Z.: Coh-Metrix: Analysis of text on cohesion and language. *Behavior Research Methods, Instruments, & Computers* 36, 2 (2004), 193–202. doi:10.3758/BF03195564. 1, 2
- [KJW\*14] KOCH S., JOHN M., WÖRNER M., MÜLLER A., ERTL T.: VarifocalReader – in-depth visual analysis of large text documents. *IEEE Transactions on Visualization and Computer Graphics* 20, 12 (2014), 1723–1732. doi:10.1109/TVCG.2014.2346677. 2
- [KPMS19] KLEIJN S., PANDER MAAT H. L., SANDERS T. J.: Comprehension effects of connectives across texts, readers, and coherence relations. *Discourse Processes* 56, 5-6 (2019), 447–464. doi:10.1080/0163853X.2019.1605257. 2
- [LMDK07] LANDAUER T. K., MCNAMARA D. S., DENNIS S., KINTSCH W. (Eds.): *Handbook of Latent Semantic Analysis*, 1 ed. Psychology Press, 2007. 2
- [MLMG10] MCNAMARA D. S., LOUWERSE M. M., MCCARTHY P. M., GRAESSER A. C.: Coh-Metrix: Capturing linguistic features of cohesion. *Discourse Processes* 47, 4 (2010), 292–330. doi:10.1080/01638530902959943. 1, 2
- [Nav09] NAVLANI A.: Latent Semantic Analysis using Python. determining optimum number of topics, 2018-10-09. Accessed: March 2022. URL: <https://www.datacamp.com/community/tutorials/discovering-hidden-topics-python>. 2