Understanding the Misunderstood

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Introduction

The research on *Latent Semantic Analysis* (LSA) in the domain of natural language processing (NLP) shows the efficiency of this method (Landauer & Dumais, 1997). Nowadays the applicability in interactive semantic rich E-Learning contexts is interesting.

Future applications may use LSA techniques for automatic tutoring (Graesser et al., 1999) or automatic scoring of written essays in trainings, tests or MOOCs, which will be the way out of single-choice and multiple-choice tests in interactive learning environments.

Text understanding is central in interactive learning environments. For this a written essay is a much better indicator than single or multiple choice questions and answers. The question of rating *if a text has been understood* is followed by the more important question of what has not been understood within the text, so that intelligent feedback can be given.

LSA can see if knowledge has been decoded into a written essay or not. If textual information is not included, it is still unclear whether the information was not understood or just not activated enough (Anderson, 1976).

Methods

In our study, we try to use LSA to rate text understanding combined with a new method of classifying paragraphs by online-highlighting within the existing pdf-file.

Participants

The study was realized with 16 German participants (11 female; mean age 22,5 years).

Procedure

In a first part the participants had to read the scientific paper *"What Benefits do the Findings of Brain Science have for Pedagogics?"* (*9 pages, 51 paragraphs, 6495 words*) in a specially programmed online pdf-reader and their task was to highlight *important and difficult parts* of the text within the pdf-file. The paper was displayed by a PDF-Viewer, which was extended in two ways. The first extension added the ability to highlight the text in two colors whereas the second extension enabled the students to store the marked text on the server. Both marks were different in color, a blueish color marked parts of the paper students thought to be of central importance and a reddish color to mark difficult parts. Their time was limited to the end of the session, which meant about 60 minutes, to read and mark the text. There was no guideline as to whether the participants should first read and mark afterwards or do both simultaneously. The participants were not especially instructed to learn the paper and there was no information given about following tasks.

One week later all participants had to reconstruct the paper by writing an essay within a special online text-editor.

Results

The latent semantic space was reduced to 21 dimensions and no weight functions were applied. Cosine was used to calculate the similarity between students' summaries and the paragraphs of the paper. Regarding the text length, four groups are appropriate to analyze (*words<100; words=101-200; words=201-300; words>300*).

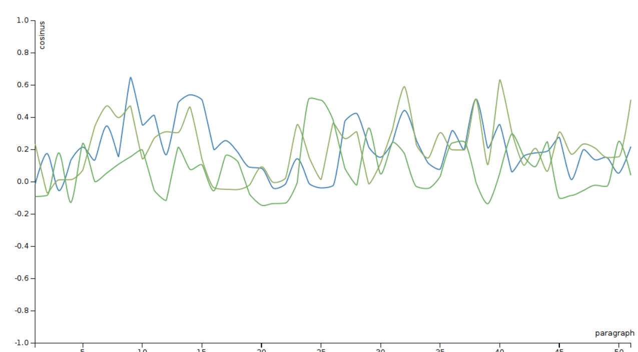

Figure 1: The cosine parameter for three participants with more than 300 written words.

Well decoded paragraphs are significantly differentiated from ill decoded paragraphs. The reason why the performance of text reconstruction differs this way lies in the text-structure itself, which can be more analyzed by autocorrelation, and in the previous knowledge of the participants, which can be analyzed within the highlighted text areas.

The autocorrelation of paragraphs presents the semantic relatedness of the paper very well.

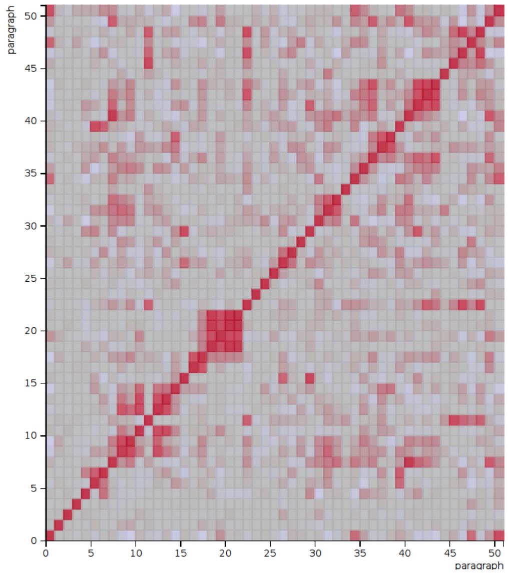

Figure 2: The 51 paragraphs' semantic content patterns.

The 51 paragraphs show perfect patterns of their semantic content. Very special paragraphs can be identified immediately (e.g. paragraph 12 about the *amygdala*).

The previous knowledge of the participants is incorporated in their highlighted text areas. The participants marked 18.87 % of the paper as of central importance and 1.4 % as opaque on average. Most (9 of 16) participants marked nothing as opaque. Exactly one student marked more opaque than as of central importance.

Table 1: Length (words in total) of the written essays and of the highlighted words

	Essay		Important		Difficult	
1	355	5.47%	627	9.65%	68	1,05%
2	221	3.40%	1138	17.52%	0	0%
3	204	3.14%	1778	27.37%	0	0%
4	104	1.60%	649	9.99%	840	12.93%
5	36	0.55%	1044	16.07%	0	0%
6	58	0.89%	1480	22.79%	0	0%
7	107	1.65%	1084	16.69%	33	0.51%
8	413	6.36%	327	5.03%	0	0%
9	321	4.94%	2170	33.41%	357	5.50%
10	170	2.62%	1420	21.86%	0	0%
11	55	0.85%	113	1.74%	0	0%
12	117	1.80%	2028	31.22%	33	0.51%
13	75	1.15%	1534	23.62%	0	0%
14	35	0.54%	1563	24.06%	91	1.40%
15	220	3.39%	1303	20.06%	30	0.46%
16	136	2.09%	1347	20.74%	0	0%

Discussion

LSA is a promising method for generating intelligent feedback in online courses and other E-Learning environments. For generating a more differentiated feedback in those systems, additional information is needed. Therefore, special highlighting methods could be introduced. Those techniques are still in development and special trainings for participants are needed to make them a standard tool in educational contexts.

References

Anderson, J. R. (1976). *Language, Memory and Thought.* New Jersey: Lawrence Erlbaum Associates.

Graesser, A. C., Wiemer-Hastings, K., Wiemer-Hastings, P., & Kreuz, R. (1999). AutoTutor: A simulation of a human tutor. *Cognitive Systems Research*, 1(1), 35–51.

Landauer, T. K., & Dumais, S. T. (1997). A Solution to Plato ' s Problem : The Latent Semantic Analysis Theory of Acquisition , Induction , and Representation of Knowledge. *Psychological Review*, *104*(2), 211–240.

Tobinski, D. A. (2014). Semantic Heat Map. *Unpublished paper.*