How Useful are Semantic Links for the Detection of Implicit References in CSCL Chats?

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***Abstract*—Chat conversations are used for a large range of Computer-Supported Collaborative Learning (CSCL) tasks especially because they allow the creation of multiple conversation threads that run in parallel. Thus, several different topics can be debated at the same time, fostering the exploitation of different ideas and facilitating collaborative knowledge creation. In order to detect these threads, our method proposed to firstly detect the links that arise between the utterances of a conversation. From a computational linguistics perspective, there is a wide variety of different types of links between utterances and there is no mechanism to compute all of them. This paper proposes to explain to what degree semantic similarity measures from Natural Language Processing (NLP) may be used to detect the links that arise between utterances in CSCL chat conversations and which is the effectiveness of applying solely this technique for implicit links identification.**

Keywords—Chat Conversations, CSCL, Natural Language Processing, Semantic Relatedness, Latent Semantic Analysis, Implicit Links

I. INTRODUCTION

Chat conversations are used in a large range of Computer-Supported Collaborative Learning (CSCL) activities, especially for debating and solving difficult problems [1]. One of the supposed reasons for the successful integration of chats in many CSCL tasks is that they allow the existence of parallel discussion threads that inter-animate throughout the discussion [2].

Discourse analysis does not provide a theory suitable for processing multi-party conversation chats. However, there are some new theories that propose the use of conversation or coherence graphs for chat analysis [1, 2]. At the base of these theories is the existence of a multitude of links – explicit or implicit – between utterances that might explain the evolution of the discussion threads. These links have been primarily connected with the notion of *outer voices* or *echoes* introduced by Bakhtin's dialogic theory [3]. This model also defined the notions of heteroglossia, inter-animation and polyphony in discourse [3, 4], and it has been proposed by some researchers as a new theory of learning to be used for any CSCL task [5]. This learning theory is applied mainly to text-based collaborative learning situations where utterances can be associated with voices. Thus, the study of the "participants' voices (and the voices within their voices)" [5] acknowledges that each utterance has an inner or specific voice of the participant which uttered it, but also complex echoes from previous voices. Determining and analyzing this linkage between voices would provide a powerful method for analyzing learning and knowledge building both at an individual level, but also at the group level (e.g. social influence or collaborative knowledge construction).

Furthermore, there have been studies that showed the existence of a connection between dialogism used for learning and thinking skills: the quality of individual thinking can be improved by improving the quality of dialogue (online and offline) and that "individual thinking skills originate in conversations, where we learn to reason, to evaluate, to join in creative play and to provide relevant information" [6]. However, the main difficulty is to determine the quality of a conversation, especially in online multi-party discussions. We have proposed that the degree of inter-animation in a conversation can be used to assess its quality [2] especially due to the fact that inter-animation assumes that meaning arises not from a single utterance, but rather from the interaction between them. This interaction between utterances is an important aspect in collaborative learning.

Thus the focus is not on the individual participant or utterance, but on the inter-play that appears between different utterances and between different participants. Inter-animation and polyphony have been previously proposed for assessing the quality of problem solving tasks using chat conversations [2, 7] or for detecting pivotal moments in online discussions by identifying the changes in the degree of inter-animation throughout a discussion [8]. Moreover, inter-animation has been also linked to meaning making [9] and knowledge building [10] activities.

The inter-animation of voices in a conversation may be represented through the *links between the utterances*, either explicit or implicit. In many conversation environments, such as online discussion forums, and special chat systems developed for CSCL, the participants are able to highlight *explicitly* one or more previous utterances the current one is responding to. However, many links to antecedent replies remain *implicit*, either due to the fact that the participants are not always using the explicit referencing feature, or because the current utterance is linked to many previous ones and it is difficult to link explicitly to all of them. Determining the inter-animation in a conversation is related to finding the implicit links (or references) between its utterances.

However, the discovery of these implicit links is a difficult task, mainly because of the multitude distinct types of links that may arise in a multi-party chat conversation [11]. For example, links can arise at different NLP levels: lexical links, continuation of utterances (which may be considered broken utterances or syntactic links), semantic links, and pragmatic and conversation specific references. All of these different types of links and some computational linguistics methods for detecting them are presented in [11].

This paper will focus on providing an answer to a rather simpler and more specific research question: "*How useful is semantic similarity alone for detecting links arising in CSCL chat conversations?*" Knowing the answer to this question, we can then move on to different and more complex types of references, together with more complicated NLP processing for detecting them. This question is of particular interest because many CSCL applications that are processing either conversations or written texts (e.g. summaries, essays, etc.) are mainly using different similarity relatedness methods (presented in the next section) for assessing the cohesion of the analyzed texts. However, they may miss important links that are not detectable using semantic similarity alone and this is the most important result of this work.

The outline of the paper is the following: section 2 presents the different methods that can be used for assessing the semantic similarity between words and even utterances. In section 3 is introduced a small corpus with multi-party CSCL conversations for which we present statistics about the explicit links available in these discussions. Section 4 offers several results and statistics on how useful is the semantic similarity alone to detect the explicit links in the conversations from out corpus. The paper ends with concluding remarks about the scope and effectiveness of using semantic similarity for detecting references between utterances.

II. Links Based on Semantic Similarity Between Utterances

Semantic relatedness between proximal words is one of the characteristics of the context in most coherent discourses, revealing the meaning of any word. Therefore, semantics in linguistics is related to determining the meaning or interpretation of any occurrence of a lexical item. In any language, genre or discourse a word's true meaning can only be understood in its context, as it may interconnect with other meanings specific to that specific language, genre or discourse.

The problem of understanding and assessing the semantic information underlying in any spoken or written discourse has been widely researched from the beginnings of the Artificial Intelligence research. However, although several methods have been proposed for solving this problem, there is no consensus about the most suitable one even in our days. In this context, there is a need to employ a diversity of techniques for assessing the semantic relatedness of words and phrases. A first differentiation between the various methods would be to classify them in "*strong*" semantics and "*weak*" semantics. The strong semantics techniques rely on general, domain and discourse ontologies [12]. Especially with the development of the Semantic Web, several general or upper level ontologies (e.g. DOLCE, CYC, DBpedia) have been developed and they can also be used for discourse processing.

However, during the last two decades other methods for computing the relatedness of words have been developed starting from exploiting the proximity information available in the large volumes of discourse corpora, especially texts, which have been published online or have been digitized using Optical Character Recognition (OCR) technologies. These methods may be called weak semantics because they do not define any underlying semantic model between the words or concepts, but rather exploit the probability distribution and the statistics of two words co-appearing together in a given discourse unit (adjacent words, sentence, paragraph, document, etc.). As the strong AI methods for semantics need a knowledge base or an ontology developed by specialists (e.g. linguists, domain experts, etc.) they are also called *knowledge-based methods*. On the other hand, the statistical "weak AI" semantic models only require a large volume of corpora in order to compute the relatedness of any two words and are therefore known as *corpus-based methods*.

A. *Knowledge-based Methods for Semantic Similarity*

These methods primarily use lexical resources built by linguists, for example dictionaries, thesauri and lexical ontologies [13]. The use of dictionaries, such as the Longman Dictionary of Contemporary English (LDOCE), or thesauri, as the Roget-structured thesauri, provides the simplest knowledge-based methods for computing similarity between words by turning these resources into simple networks through the use of headwords in LDOCE or categories and indexes in Roget thesauri. A simple method for computing the semantic relatedness of two words based solely on their lexicon definitions is the Lesk measure defined for word sense disambiguation [14] that is proportional to the number of common words in the two definitions.

However, the most popular methods for computing the semantic similarity or relatedness between two words or concepts are defined for ontologies. Most of them have been especially constructed for the linguistic ontology (or lexical database) WordNet [15] and make use of the different types of relations defined in it: synonyms, antonyms, related words, hypernyms, hyponyms, meronyms and holonyms. However, they are also working for other semantic networks and upper level ontologies.

B. *Corpus-Based Methods for Semantic Similarity*

These methods have been widely used in the last years as a complement and even as an alternative to knowledge-based methods for computing semantic relatedness. Instead of using human-assembled linguistic knowledge, these techniques process large amounts of text (or other type of discourse) corpora and then use the statistics of words co-appearances in a given unit of analysis (utterance, paragraph, whole document, web page, etc.).

Latent Semantic Analysis (LSA) [16] is such a technique that has been successfully used for many NLP tasks, including computing the semantic similarity. It uses a singular value decomposition (SVD) in order to reduce the dimensionality of the term-document matrix computed for all the texts in the analyzed corpus. Thus, after performing SVD on the term-document matrix, the dimensionality of the diagonal matrix composed of the singular values is reduced to contain only the most important *k* elements. These are the largest singular values, with *k* usually chosen between 100..300, although slightly greater values may be used for specific tasks and large corpora. This reduced dimensionality space is also called the *latent semantic space* and may be used to compute the similarity between words, word sets and texts by using cosine similarity for the document vectors in this reduced space.

III. The Distribution of Explicit Links in a Corpus of Multi-party CSCL Chats

Some of the tools used for online discussions allow the usage of references between different utterances. Because these links (references) are added by the users when they are issuing a new utterance (chat reply, post, comment, message, tweet, etc.), they are called *explicit* especially due to the fact that the user had the option to explicitly select a previous utterance and connect to it. However, in most cases each utterance can only be explicitly linked to a single previous one. This is usually the case of discussion boards or forums, but there are also chat environments, such as ConcertChat [17], that provide the same facilities.

The role of explicit links is to guide the conversation and simplify the context of an utterance for the other participants in the discussion. Moreover, explicit links may also be used to structure conversations into threads that are similar to the ones in online discussion forums. In multi-party online conversations explicit links play an even more important role than in other types of discussions due to the fact that multiple conversation threads arise naturally. Moreover, in many cases it would be useful to be able to explicitly select more than a single utterance as a reference for the current one. This is the case especially the case for online chat conversations, but also discussion forums, used for problem solving and other complex learning tasks. Furthermore, in most other conversations, both online and face-to-face, either written or spoken, there are utterances that are referring or continuing one or several previous ones. However, using such a system would become difficult and at this moment there is no popular technology that permits this functionality.

For our study, a small corpus consisting of 8 chat conversations has been analyzed in order to compute some statistics with regard to (explicit and implicit) links' usage and to provide examples from real world conversations. They represent conversations of students following the Human-Computer Interaction course from the Department of Computer Science. The students have to debate which is the best web tool for collaboration within a company and then to discuss which tools they would propose to be used by that company for certain tasks [18]. All the discussions were performed using ConcertChat, one of the tools designed especially to support CSCL tasks and which allows the use of explicit references.

In order to understand how implicit links work, studying the statistics of the usage of explicit links in these real-world conversations may provide useful information. To start with, Table 1 provides basic information about the chats: the number of utterances, the number of explicit links used by the participants and the ratio of explicit links per utterance. These results may be extrapolated for other multi-party chat conversations especially if they are created in an educational context. The average ratio shows that more than two out of three utterances (68%) are using an explicit reference to denote its interaction with one of the previous turns.

TABLE I. The Usage of Explicit Links in a Corpus of 8 Multi-party Chat Conversations

Chat ID	Number of explicit links	Number of utterances	Explicit links per utterance
Chat-131	340	430	0.79
Chat-132	296	350	0.85
Chat-133	181	296	0.61
Chat-134	207	261	0.79
Chat-135	240	392	0.61
Chat-136	188	284	0.66
Chat-143	284	419	0.68
Chat-an5	176	381	0.46
Total / average	**1912**	**2813**	**0.68**

The complete distribution of explicit links given the distance between the two utterances and computed on the data presented above is displayed in Fig. 1. Moreover, a 6-degree polynomial trendline that matches the data almost perfectly is also depicted. From this distribution it is easy to observe that over 60% of the explicit links are towards one of the previous 3 utterances and that more than 95% of them are pointing to one of the previous 10 utterances in the conversation. The analysed data should be representative for multi-party chat conversations with 4-5 participants that are engaged in collaborative learning or problem-solving activities as it contains over 2500 utterances and 1900 explicit links.

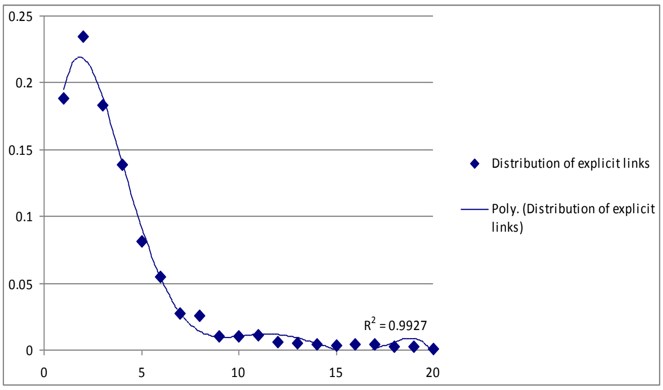

Fig. 1. Distribution of explicit links used in 8 chat conversations with 4-5 participants and a total of over 2500 utterances

The analysis of the distribution of explicit links should also be useful when trying to identify the implicit links that arise naturally between utterances. However, not all these results can be extrapolated to implicit links and several points must be kept in mind:

- Many references that point to the most recent utterance in the conversation may have not been explicitly pointed out by the participants due to the fact that usually in chat, as in other types of dialogues, it is accustomed to continue the current discourse by “linking” to the previous utterance. This is also true in most conversations, either online or face to face, with only two interlocutors: even if the current utterance bears the echoes or influences of other utterances as well, most frequently the previous utterance has the most important influence.
- There may also be explicit links to utterances that are at a close distance (2-5) that have not been pointed out for various reasons, but they are not as frequent as in the previous case.

The existence of an explicit link does not guarantee that the influence between the two adjoined utterances is greater than another connection left implicit. The participant always has to choose the explicit reference during a discussion that is unfolding in a rapid rhythm and sometimes this may be rather challenging. It is important to keep in mind that even a human participant may sometimes not be able to choose the best option when so many variants are available.

IV. Are Semantic Links Useful for Analyzing CSCL Chat Conversations?

In this section we are analyzing to what degree different semantic similarity measures can be used to explain the (explicit and implicit) links that arise between utterances in multi-party chat conversations. We are performing a study on two different levels. The first one is at the macro-level to detect whether there is a link between the distribution of explicit links and the one of the average semantic similarity between two utterances. Second, at a micro-level, we are looking at how semantic similarity can be used to discover the links in chat conversations and how useful is the use of this technique alone.

A. Macro-Level Analysis

As we already have a corpus of chat conversations with explicit links, we first wanted to determine whether semantic similarity measures are suitable for explaining the choice of these links. Therefore, a first experiment was to compare the distribution of the explicit links from the previous section to the semantic similarity between the current utterance and utterances that are at a certain distance from it.

Fig. 2 shows the average semantic relatedness scores computed using Latent Semantic Analysis (LSA) on the same corpus of 8 chat conversations with 4-5 participants.

The first observation is that there is a very good resemblance with the distribution of the explicit links, with two notable differences. Firstly, the semantic relatedness scores are varying with the distance from the current utterance less abruptly, and they tend to stabilize at a slightly smaller distance (around *dist*=8, as for explicit links the cut-off can be observed at *dist*=9). Secondly, the semantic similarity is decreasing constantly with the distance until it stabilizes at *dist*=8; afterwards the various are so slight that they are just caused by chance. This differs from the distribution of explicit links where there was an increase from *dist*=1 to *dist*=2, followed by a similar decrease until *dist*=9. In conclusion, the two analyzed distributions are quite alike, except for the fact that the semantic similarity score for utterances situated at a distance less or equal to 3 varies in a dissimilar way to the explicit links’ distribution.

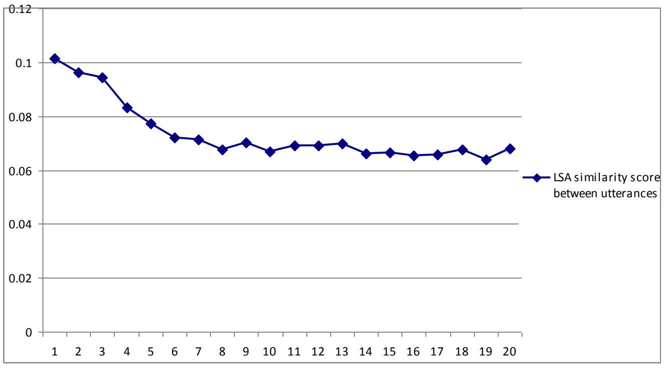

Fig. 2. The average semantic relatedness computed using LSA between the current utterance and previous ones in the 8 chats corpus

The next step of the research was to determine if these results are dependent on the measure used for computing the semantic relatedness between the utterances. Thus, LSA was replaced with a knowledge-based method by using several semantic distances computed using WordNet. To this extent, a first remark is that some of the words used by the students in the chat conversations do not appear with those specific senses in the English WordNet. This is visible especially for words expressing web technologies used for collaboration. For example, while *chat* and *forum* are present in the lexical database, but with other more usual senses, concepts like *wiki* and *blog* are completely missing. Moreover, word sense disambiguation was not performed due to the difficulty of this task especially when using online conversations that have a different language model and style. Thus, we have preferred to use the “*all senses*” approach offered by the WordNet Similarity API (http://code.google.com/p/ws4j/) that computes the similarity between all the senses for a given pair of words and then uses the maximum value as the final score [19].

After computing the semantic similarity between all pairs of words in the chat corpus, the similarity between two distinct utterances has been computed using a formula designed for assessing the sematic relatedness of any two text documents [20]. In (1), the two texts – in our case, utterances – are *T1* and *T2*, *idf(w)* is the inverse document frequency of a word *w* from one of the two texts, while *maxSim(w, T1)* is the maximum similarity between a given word *w* in the document *T2* and any word in the document *T1*:

$$sim(T1,T2) = \frac{1}{2} * \left(\frac{\sum_{w \in T1} (\max Sim(w,T2) * idf(w))}{\sum_{w \in T1} idf(w)} + \frac{\sum_{w \in T2} (\max Sim(w,T1) * idf(w))}{\sum_{w \in T2} idf(w)} \right) \quad (1)$$

The results obtained using the semantic similarity measure proposed by Resnik [21] for one of the chat conversations in the analyzed corpus are presented in Fig. 3. The evolution is similar to the one obtained with LSA: there is a decrease of the similarity with the distance between utterances which stabilizes at a distance of 8 or 9. However, the semantic similarity scores are slightly higher using Resnik's similarity measure for WordNet (varying from 0.15-0.21) than when using LSA (which are in the interval 0.06-0.11) for utterances situated at any distance between 1 and 20. Therefore, the first conclusion after using this macro-level comparison is that both LSA and WordNet-based similarity measures are useful for capturing links between utterances and that both of them express a similar distribution with the explicit links.

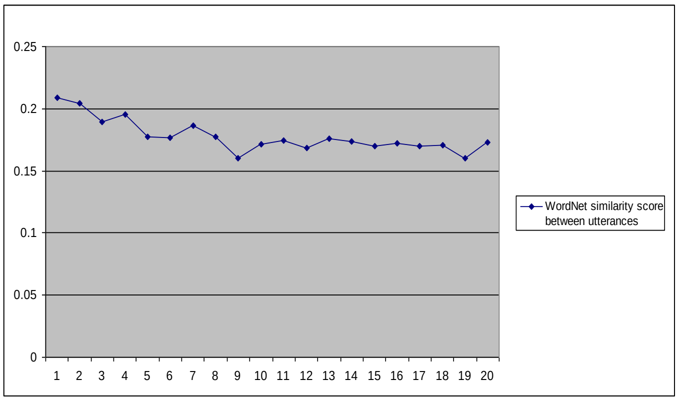

Fig. 3. The average semantic relatedness between the current utterance and previous ones in the 8 chats corpus computed using Resnik similarity

B. *Micro-Level Analysis*

Next, we are presenting a preliminary study on how effective LSA-based semantic similarity is for the detection of links between utterances from our chat corpus. We propose to determine this effectiveness by investigating whether semantic similarity can be used for the detection of explicit links and to what extent this method is useful.

In Table 2 are several fragments of a chat conversation together with the explicit links used by the participants and the results of using LSA-based semantic similarity as a criterion for automatically selecting the most appropriate (implicit, because we consider it to be determined by our method without any explicit cues being used) reference to a previous utterance. The rule was very simple: for each utterance there is an (implicit) link to one of the previous 20 turns that has the highest similarity score with the current one. The rightmost column shows the highest such score for the utterances presented in the table, thus being able not only to point out several of the explicit links, but also to determine a new implicit link. An interesting remark is that, using this approach, links that span over 11 utterances are correctly identified (e.g. the link from turn 166 to turn 155). On the other hand, it is clear that not all explicit links can be identified using just the semantic similarity score, especially the ones that depend on pragmatic and conversation-specific elements (e.g. adjacency pairs, signaling turns and others).

TABLE II. SEMANTIC SIMILARITY SCORES COMPUTED USING LSA FOR DETERMINING THE LINKS

ID	Utterance	User	Link	Sematic score
148	ok.... so what we were talking about before the connection issue?	Mona		
149	as long as it depends on an internet connection...	Mona	LINK TO 147	
150	meeting board	Cristi	LINK TO 148	score(150, 148) = 0.18 = max
151	about different stages of a project... a client must know about them..so wiki is a good solution	Corina	LINK TO 148	
152	meeting?	Corina	LINK TO 150	score(152, 150) = 1.00 = max
153	ok	Stefan	LINK TO 151	
154	so we agree that wiki is a good solution when we want to present a product/the evolution of a project to a client ?	Corina		score(154, 151) = 0.5 = max
155	what about selling our products..what technologies we should use for this?	Diana		
…				
166	to sell our products blog is the best solution	Corina	LINK TO 155	score(166, 155) = 0.38 = max
…				
169	A blog would be a good way to advertise our products	Mona	LINK TO 166	score(169, 166) = 0.48 = max
…				
180	A forum would be useful for offering solutions to some problems that our customers have	Mona		
181	I agree...also other people can offer solutions, not only us	Corina	LINK TO 180	score(181, 180) = 0.27 = max

TABLE III. HOW USEFUL IS THE SEMANTIC SIMILARITY ALONE FOR COMPUTING THE EXPLICIT LINKS?

Chat ID	**References greater than 10-turn median**	**References greater than 20-turn median**	**Pearson correlation: number of references – av. semantic score**
Chat-131	0.44	0.40	0.83
Chat-132	0.47	0.47	0.90
Chat-133	0.41	0.41	0.81
Chat-134	0.45	0.47	0.88
Chat-135	0.42	0.42	0.76
Chat-136	0.43	0.45	0.92
Chat-143	0.45	0.47	0.78
Chat-an5	0.48	0.45	0.88
Average	**0.44**	**0.44**	**0.84**

Table 3 highlights this issue by presenting information about the effectiveness of using solely the semantic similarity scores computed using LSA for detecting all the explicit links in the analyzed discussions. On average, only 44% of the two utterances that are involved in an explicit link have a semantic similarity score higher than the median computed for the last 10 and 20 turns. However, there is a very high correlation (0.84) between the average similarity score and the number of explicit links at a given distance in number of utterances.

V. CONCLUSIONS

The results presented in this paper can be extrapolated to the task of detecting new implicit links in other multi-party chat conversations used for CSCL tasks. Two important conclusions arise from this study. First, the distribution of explicit links is very similar to that of the semantic similarity scores, thus proving that, on a macro-level, both links and semantic similarity measures have a similar behavior. However this is not always true when analyzing local elements: an individual link between two utterances is not always explained by semantic similarity. This result has already been highlighted in a previous publication on this topic [22]. However, the second conclusion is that only around 40% of the explicit links in our conversations could be explained based mainly on semantic similarity measures and simple greedy heuristics such as picking the highest score between pairs of utterances.

In the future, we propose to investigate which measure for expressing semantic similarity or relatedness is most suitable for determining most of the explicit links existent in our chat corpus. A preliminary research started on this topic shows that Jiang and Conrath's semantic similarity measure outperforms Resnik's [23] and Lin's [24], but also LSA-based measures, on our corpus.

Let us conclude with an answer to the question asked in the title of the paper. Yes, semantic similarity measures are useful for detecting implicit links in CSCL chat conversations, but they only account for slightly less than half of these links. The other half needs to be detected using alternative processing based on more complex discourse processing techniques that need to use a mix of syntactic analysis, coherence relations, dialog acts and pragmatic links.

ACKNOWLEDGMENT

This work has been funded by the Sectorial Operational Programme Human Resources Development 2007-2013 of the Romanian Ministry of European Funds through the Financial Agreement POSDRU/159/1.5/S/132397 and by the FP7 LTfLL project.

REFERENCES

[1] G. Stahl, Studying Virtual Math Teams, New York: Springer, 2009.

[2] S. Trausan-Matu, and T. Rebedea, "Polyphonic inter-animation of voices in VMT," Studying virtual math teams, G. Stahl, ed., pp. 451–473, New York: Springer, 2009.

[3] M. M. Bakhtin, The dialogic imagination: four essays: University of Texas Press, 1981.

[4] M. M. Bakhtin, Problems of Dostoevsky's poetics, Minneapolis: University of Minnesota Press, 1993.

[5] T. Koschmann, "Toward a dialogic theory of learning: Bakhtin's contribution to understanding learning in settings of collaboration."

[6] R. Wegerif, "A dialogic understanding of the relationship between CSCL and teaching thinking skills," International Journal of Computer-Supported Collaborative Learning, vol. 1, no. 1, pp. 143-157, 2006.

[7] S. Trausan-Matu, T. Rebedea, A. Dragan, and C. Alexandru, "Visualisation of Learners' Contributions in Chat Conversations," Blended Learning, J. Fong and F. L. Wang, eds.: Addison-Wesley, 2007.

[8] D. Suthers, K. Lund, C. Rose, G. Dyke, N. Law, C. Teplovs, W. Chen, M. Chiu, H. Jeong, C.-K. Looi, R. Medina, J. Oshima, K. Sawyer, H. Shirouzu, J.-W. Strijbos, S. Trausan-Matu, and J. van Aalst, "Towards productive multivocality in the analysis of collaborative learning," in 9th International Conference on Computer-Supported Collaborative Learning (CSCL 2011), 2011, pp. 1015-1022.

[9] P. Scott, and E. Mortimer, "Meaning Making in High School Science Classrooms: A Framework for Analysing Meaning Making Interactions," Research and the Quality of Science Education, K. Boersma, M. Goedhart, O. Jong and H. Eijkelhof, eds., pp. 395-406: Springer Netherlands, 2005.

[10] F. Rezende, and M. Castells, "Interanimation of voices and argumentative strategies in collaborative knowledge building of physics teachers in an asynchronous discussion group," Revista Electrónica de Enseñanza de las Ciencias, vol. 9, no. 2, 2010.

[11] S. Trausan-Matu, and T. Rebedea, "A Polyphonic Model and System for Inter-animation Analysis in Chat Conversations with Multiple Participants," Computational Linguistics and Intelligent Text Processing, Lecture Notes in Computer Science A. Gelbukh, ed., pp. 354-363: Springer Berlin / Heidelberg, 2010.

[12] P. Ciccarese, E. Wu, G. Wong, M. Ocana, J. Kinoshita, A. Ruttenberg, and T. Clark, "The SWAN biomedical discourse ontology," J. of Biomedical Informatics, vol. 41, no. 5, pp. 739-751, 2008.

[13] A. Budanitsky, and G. Hirst, "Evaluating WordNet-based Measures of Lexical Semantic Relatedness," Comput. Linguist., vol. 32, no. 1, pp. 13-47, 2006.

[14] M. Lesk, "Automatic sense disambiguation using machine readable dictionaries: how to tell a pine cone from an ice cream cone," in Proceedings of the 5th annual international conference on Systems documentation, Toronto, Ontario, Canada, 1986.

[15] G. A. Miller, "WordNet: a lexical database for English," Commun. ACM, vol. 38, no. 11, pp. 39-41, 1995.

[16] S. Deerwester, S. T. Dumais, G. W. Furnas, T. K. Landauer, and R. Harshman, "Indexing by latent semantic analysis," Journal of the American Society for Information Science, vol. 41, no. 6, pp. 391-407, 1990.

[17] M. Muhlpfordt, and M. Wessner, "Explicit referencing in chat supports collaborative learning," in Proceedings of the 2005 conference on Computer support for collaborative learning: learning 2005: the next 10 years!, Taipei, Taiwan, 2005.

[18] T. Rebedea, M. Dascalu, S. Trausan-Matu, G. Armitt, and C. Chiru, "Automatic assessment of collaborative chat conversations with PolyCAFe," EC-TEL 2011 - Towards Ubiquitous Learning, pp. 299-312: Springer Verlag, 2011

[19] T. Pedersen, S. Patwardhan, and J. Michelizzi, "WordNet::Similarity: measuring the relatedness of concepts," in Demonstration Papers at HLT-NAACL 2004, Boston, Massachusetts, 2004.

[20] R. Mihalcea, C. Corley, and C. Strapparava, "Corpus-based and knowledge-based measures of text semantic similarity," in Proceedings of the 21st national conference on Artificial intelligence - Volume 1, Boston, Massachusetts, 2006.

[21] P. Resnik, "Using information content to evaluate semantic similarity in a taxonomy," in Proceedings of the 14th international joint conference on Artificial intelligence - Volume 1, Montreal, Quebec, Canada, 1995.

[22] T. Rebedea, and G.M. Gutu, "Detecting Implicit References in Chats Using Semantics," in Proceedings of EC-TEL 2013, LNCS 8095, pp. 627-628, Springer, 2013.

[23] J. J. Jiang, and D. W. Conrath, "Semantic Similarity Based on Corpus Statistics and Lexical Taxonomy," CoRR, 1997.

[24] D. Lin, "An Information-Theoretic Definition of Similarity," in Proceedings of the Fifteenth International Conference on Machine Learning, 1998.