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Sentiment-Based Assessment Of Electronic Mixed-Motive Communication - A Comparison Of Approaches

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SENTIMENT-BASED ASSESSMENT OF ELECTRONIC MIXED-MOTIVE COMMUNICATION – A COMPARISON OF APPROACHES

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Abstract

In this paper, we seek to analyse specific types of bilateral electronic communication processes, namely such processes where there is a distinction between individual goals of the communicating parties and their joint goals. We argue that there exists a distinction between successful and unsuccessful processes. This distinction is manifest in the communication patterns used by the participants. Sentiment analysis can enable researchers to identify these distinctions automatically, based on a classification model previously trained for the exact type of communication process. This paper discusses an adaption of sentiment-based techniques for the domain of electronic business negotiations.

Keywords: sentiment analysis, electronic communication, negotiation, mixed-motive interaction

1.0 Motivation – Mixed-Motive Communication Processes

A mixed-motive communication process is characterized by the interplay of each participants' individual goal and all participants' joint goals (Komorita and Parks 1995). In such a scenario, parties communicate their intentions via their evaluation of the other parties' statements, as well as via disclosing pieces of information about their own intentions. Since joint goals can only be reached if all communicating parties in the end agree to a specific result of the discussion, there is an inherent difference between mixed-motive processes that are successful and those that are unsuccessful.

In an electronic scenario, where the parties do not have visual or aural access to each other (e.g. using e-mail), the role of exact language usage increases to a level, which is crucial for the success of said processes, because of the absence of other communication channels (Walther and Parks 2002, Berger 2002). Therefore, we argue that there exists a clear difference in the language (i.e. choice of words) of successful and failing interactions. This point of view is, to a degree comparable to basic assumptions of Discourse Analysis (Bavelas et al. 2002) especially to the approach that language acts as a manifestation of mental processes of the utterer, as a means to explicate individual goals, while at the same time respecting the joint goal of the interaction and the individual goals of the communication partner. If an actor in such a communication process perceives a violation of his/her individual goals, the interaction may end in disagreement and impasse.

The present paper seeks to analyse such mixed-motive communication processes through the application of techniques from Sentiment Analysis. The authors' point of view is that each turn in the course of such an interaction (in our case, written, asynchronous, electronic communication) can be seen as an opinionated document containing evaluative, polar statements about the different dimensions of the interaction process (i.e. the interaction topic, personal evaluations of the communication partner, etc.). We expect a difference in the polarity distributions between successful and failing interactions, especially in the form of a "foreshadowing" of failure. Since reasonably well-constructed Sentiment Analysis applications are used in an automated manner, this detection mechanism could enable computer systems to recognize failing interaction at an early stage, and potentially intervene in order to prevent said failure. Apart from the different polarity distribution, we expect interactions to differ in their sentiment expression with respect to "2nd order outcomes", e.g. the subjectively experienced quality of the interaction, social relationship formation process as well as the degree of trust established between the communicating parties.

As a main exponent of such communication processes, we will look into the area of negotiations, in our case business-to-business negotiations conducted asynchronously in an electronic manner using a negotiation support system (NSS). Therefore, we will present a brief overview on the communicational influence on negotiation outcomes, then outline details of the application of sentiment analysis methods before introducing four variations of sentiment assessment we applied in the course of our research. These methods, and probably solutions integrating multiple of the methods are to be evaluated using a dataset of experimental negotiations created in December 2013. The main research goals that are to be followed in the course of this paper are:

To which degree are methods of sentiment analysis applicable to complex communication interactions?

How are sentiment-based assessments of negotiation interactions linked to common outcome variables of negotiations, such as success or failure of the negotiation (i.e. negotiations resulting concluding in agreement with a final contract or negotiations resulting in an impasse where there is no outcome), substantive outcomes (individual and joint utilities) as well as satisfaction of the negotiators?

2.0 Analysis – Communication and Negotiation Outcomes

The influence of negotiators' communication behaviour on negotiation outcome variables is one that has been widely discussed in negotiation literature. In most cases, a sub-construct and its facilitation through communication methods are analysed such as the cognitive or the behavioural role of communication. There exists a large body of research on the affective element of communication, such as the conveyance of positive or negative emotions (e.g. Liu et al. 2010, Hines et al. 2009, Martinovski 2010).

These communicative dimensions have commonly been linked to the economic as well as the relational outcomes of the negotiation process. It has even been argued that the communicational content in early phases may have a distinctive influence on negotiation outcomes (e.g. Lewicki et al. 2010, usage of affective persuasion in Adair and Brett 2005, also Simons 1993).

Duckek (2010) developed a model that links effects of communication quality to relational as well as to substantive outcomes of the negotiation process. The model evaluates communication quality as a result of grounding, coherency of the communication process and relational communication. Applied in the context of electronic negotiations it has been shown that failing negotiations are characterised by a lowered mutual understanding between the negotiators, less friendly communication and a tendency to avoid compromises. Conversely, a higher negotiation quality results in increased satisfaction and an increased level of trust between the negotiators.

Liu et al. (2010) distinguish three negotiation communication dimensions, namely clarity, responsiveness and comfort. Clarity encompasses the negotiators' understanding of the negotiation situation, facilitated by the degree to which information is exchanged, and the resulting negotiators' ability to identify trade-offs and integrative potential in the negotiation situation. Similar to preceding research on information sharing (e.g. Adair et al. 2004) Liu et al. report that a higher level of communication clarity increases joint gains in negotiation situation as well as the satisfaction of the negotiators with the negotiation process and outcome. The second dimension identified is responsiveness, which encompasses engaging in integrative behaviour, communication of concern and more generally, communication of one's own reflection on the partner's perspective. Likewise, a higher responsiveness tends to yield higher joint gains and higher rates of satisfaction.

The last dimension, similarly linked to joint gains and satisfaction is comfort, consisting mostly of the emotional state of the negotiators and the affective communication they interchange. This dimension is especially interesting from a sentiment analysis point of view, as will be laid out in the following chapter. Liu et al distinctively point out the negative effects of a low-comfort situation on negotiation outcomes and negotiator satisfaction (as also argued in van Kleef 2009), consistent with previous findings such as Hines et al. (2009) who argue that displaying positive emotions can be predictive of negotiation success (see also Martinovski 2010). Also, the display of emotions such as happiness and anger can distinctively alter the negotiation partner's concession behaviour, depending for example on the general integrativeness of the negotiation task, the substantive (i.e. concession) behaviour that accompanies the displaying of emotions and whether the recipient of the emotional reaction deems it to be appropriate in the given situational context (van Kleef et al. 2004).

It is, furthermore, important to discuss the role of the affective dimension of communication when we switch from a face-to-face scenario, where the negotiators can directly see and talk synchronously to each other to an electronic situation where the negotiators merely communicate in an asynchronous dislocated, and – as is the case in this study – written manner, without the possibility to see or hear each other. There is an extensive body of discussion on how social interactions are shaped by the medium through which they are conveyed. The common course of the debate sees two opposing positions, which have been subsumed by Walther with the terms "cues filtered out" and "cues filtered in" (Walther and Parks 2002).

The "cues filtered out"-perspective is theoretically rooted in the Social Presence Theory (Short et al. 1976). The basic notion introduced by this theory is that interpersonal communication is conveyed via different communication channels. These channels can be distinguished as verbal and non-verbal channels. Whilst verbal channels convey the factual content of an utterance, non-verbal channels provide the listener with additional information, such as gestures, facial expressions, or the tone of voice. The fewer channels are available, the lower the likelihood of creating an interpersonal relationship. Communication becomes de-personalized, since the “social presence” of the individual decreases (e.g. Kiesler et al. 1984). According to this approach, electronic communication, especially in a written-only, asynchronous scenario such as the one used in this study, would not allow for the conveyance of affective communication.

However the counter-perspective, known as “cues filtered-in” argues that even though there are fewer communication channels in the notion of Short et al., the importance of the information transported via these channels increases and becomes more salient for the interpretation of an utterance. Additional ways to transmit social cues are developed and imposed on the remaining channels (such as, for example, inflectives or emoticons in internet communication). Social Information Processing Theory (Walther 1992) furthermore states that although social relationship development is more difficult in a reduced-channel scenario, it nevertheless is possible to the same degree as in a face-to-face-situation – the only factor that increases is the time needed for development.

In the context of electronic negotiations, the latter notion is for example confirmed in an exploratory manner by Griessmair and Köszegi (2009). According to their findings, emotion is carried in a less explicit manner via the asynchronous negotiation message but there is an implicit emotional layer to electronic negotiation communication which is even conveyed by factual statements. Nevertheless, the explicit linguistic manifestation of these statements remains important for their interpretation (cf. Martinovski (2010)). Finally, there are differences in the development of affective communication patterns between successful and failing negotiations, which again emphasizes the crucial role of communication for negotiation success. Electronic and face-to-face negotiations show similarities in the linguistic traits Sokolova et al. (2006).

Albeit the decision-theoretic perspective on negotiations (i.e. the factual, rational quality of offers exchanged and concessions made), communication of offers plays a crucial role concerning negotiation outcomes, identification of integrative potentials, and negotiator satisfaction with the negotiation process as well as with the negotiation outcomes.

There exist different attempts to formalize and simplify communication analysis, similar to the method described in this paper. In fact, most of the manual methods used, do exactly fulfil this task. A common example in the context of (electronic) negotiations is Content Analysis (e.g. Srnka and Köszegi 2007). Negotiators' utterances are separated into single "units of thought" and then manually classified into a predefined category scheme; the exact form of this scheme often depends on the research question that is to be answered by the analysis process. There exists an attempt to automate the process of content analysis using machine learning techniques (Nastase et al. 2007), but with rather unsatisfactory results, most likely due to the high amount of classes used in the classification problem.

Automatic prediction of negotiation success based on communicational content has also been tried in recent years, with varying success. Twitchell et al. (2013) manually code data from divorce negotiations into integrative and distributive speech acts. This coded data is then used to train a machine learning scheme to distinguish between success and failure of a negotiation, reaching an accuracy of up to 85%.

Sokolova and colleagues use a linguistic approach to analyze differences between successful and failing negotiations, first focusing on modals, pronouns, mental verbs and simple positively and negatively connotated verbs as well as expressions of negation (Sokolova and Szpakowicz 2007), and later on determining an informativeness rating for the message based on the usage of words of degree, scalars and comparatives (Sokolova and Lapalme 2012). Their findings report significant improvements in classification accuracy over the baseline.

3.0 Common Sentiment Analysis Approaches

Sentiment analysis (also referred to as Opinion Mining) has been an emerging research field during the past ten years. The aim of sentiment analysis is the *analysis of opionated texts*, i.e. documents of any kind that convey the subjective opinion of the writer and are designed to be subjective and evaluative. The research field has obviously received great attention in recent years with the emergence of the Web 2.0 and the massive increase in publicly available, user-generated, opinionated documents.

The original and most common domain of sentiment analysis is customer reviews on products in online shops such as amazon.com (e.g. Kanayama and Nasukawa 2012). In addition, sentiment analysis has been used in a wide range of different domains, such as movie, hotel and restaurant reviews (e.g. Ganu et al. 2013), blog posts (e.g. Zhang et al. 2009), tracking of political opinions and determination of election results (e.g. Lu and Zhai 2008), stock market development determination (Das and Chen 2007), e-mail communication (Mohammad and Yang 2011) and brand sentiment tracking via Twitter (Mostafa 2013).

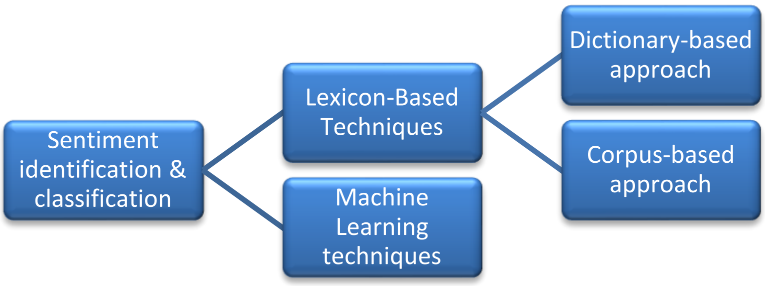

Figure 1: Elementary sentiment classification approaches

One of the core tasks in sentiment analysis is polarity classification of texts or text fragments, commonly into the two simplified dimensions *positive* and *negative* (Liu 2012, Pang and Lee 2008). As Figure 1 shows, existing methods to conduct this task can roughly be classified into two subfields. Firstly, there are the methods that apply (and sometimes generate) a specific *Sentiment Lexicon* for the evaluation of terms and phrases occurring in the document to be classified. The generation of these sentiment lexica is typically distinguished into two approaches, the dictionary-based approach and the corpus based-approach. Secondly, there are the methods that rely on a trained machine learning model. Since both of these methods will be applied in the course of this paper, the following section is dedicated to explain them in further detail.

The type of method to be applied on a specific sentiment classification problem mainly depends on the granularity of the classification task, i.e. types of granularity, classification on document level, sentence level, and aspect level (Liu 2012). We will focus on classification on sentence level and on aspect level here, since we expect a negotiation document to contain a multitude of differing opinions on certain aspects of the negotiation.

Machine learning-based techniques model sentiment classification as a typical supervised text classification problem. Most commonly, it is applied on sentence-level granularity. Starting from a predefined set of classes (typically positive, negative, and neutral), human coders assign these classes to a training set of sentences for the chosen domain of application. This set is then used to create a classification model using common text classification techniques for preparation of the dataset and for dimensionality reduction and feature vector creation such as stemming, lemmatization, stopword filtering etc. (for an extensive overview on these methods, see for example Manning et al. 2008, Feldman and Sanger 2007, Sebastiani 2002).

Apart from the supervised learning methods, some researchers use lexicon-based techniques combined with different scoring methods for sentences (Hu and Liu 2004). Lexicon-based methods rely on sentiment evaluation using and sometimes also constructing a *Sentiment lexicon*, i.e. a lexicon of words that are considered to indicate positive or negative expressions in the domain the lexicon is generated for. Before scoring or classification steps can be performed, a sentiment lexicon has thus to be constructed. Whilst there are general-purpose sentiment lexica (e.g. Hu and Liu 2004; Wiebe et al. 2005; Baccianella et al. 2010), domain-specific lexica are deemed to be better for polarity assessment accuracy.

Liu (2012) distinguishes three different approaches to create a sentiment lexicon: The corpus-based approach, the dictionary-based approach and the manual approach which, due to its labour intensity, is very rarely used alone, but rather in combination with one of the other approaches.

The *dictionary-based approach* is an automated way to generate a sentiment lexicon, which is based on synonym and antonym-searches in dictionaries. Starting from a short list of seed words with a given polarity (defined by the researcher), synonym and antonym lists are obtained from online dictionaries such as WordNet (Fellbaum 1998). Similarly, terms that tend to co-occur with seed words can be obtained through online searches (Turney and Littman 2003 use AltaVista's NEAR-Operator to perform this search). Resulting synonyms and antonyms are then assigned the respective polarity of their seed word, and are used in the next iteration. After a sufficient amount of iterations, the process stops. The benefit of this method is that no large dataset is required to construct the sentiment lexicon. However, due to the nature of the approach (i.e. – starting with a very unspecific list of seed words), the resulting sentiment lexica tend to be rather domain-unspecific.

In contrast to the dictionary-based approach, the *corpus-based approach* provides the possibility to create a sentiment lexicon with a domain-specific focus. It relies on an initial corpus of documents from the respective domain from which sentiment words are extracted. In this way, it is possible to transfer existing sentiment lexica to a specific domain (Liu 2012). The extraction of sentiment words follows a set of rules defined by the researcher. Popescu and Etzioni (2010) propose a feature-driven approach which first identifies features that are potential targets of the sentiments, and then seeks out adjectives occurring in the context of those features. A similar approach is taken by Hu and Liu (2004). Evaluation of these adjectives can be conducted manually in a human coding process or automatically using the data of existing sentiment lexica.

4.0 Application of the Approaches to Negotiation Data

We are designing and developing a program able to automatically annotate negotiation statements with respective sentiment expressions drawn from a sentiment lexicon developed for this specific context. Therefore, we used a large corpus of electronic B2B-negotiations that were conducted during the past six years in student experiments at the University of Hohenheim, using the Negotiation Support System Negoisst (Schoop et al. 2003, Schoop 2010). The complete dataset consisted of 2495 negotiation messages from 182 completed negotiations, all taken from the same experimental case, a joint venture negotiation between two companies. After we extracted the negotiation data from the respective experimental databases, a manual cleaning phase was carried out, in which we filtered negotiations that were obviously conducted in an unserious manner or – contrary to the experimental specifications – not conducted in English. The resulting negotiation messages corpus consisted of 2459 messages from 173 negotiations, of which about 75% ended successfully and about 25% failed.

In the next step, we tried to minimize the effect of the experimental case on the lexicon generation, which of course is largely attributed to aliases of the negotiators, items from the agenda or common terms that are specific for this negotiation (such as 'joint venture'). Therefore we heuristically replaced names of persons, locations and companies with a generic tag using the Named Entity Recognition toolkit Stanford NER (Finkel et al. 2005). Additionally a filtering list consisting of 165 terms that were subjectively assessed as being overly specific for a generalizable negotiation sentiment lexicon was created manually. In the later process feature candidates were ignored if they occurred in this list. Furthermore, we removed numerals from the negotiation texts. In the last preprocessing step, we parsed all negotiation messages using the Stanford Parser (Toutanova et al. 2003). which models linguistic relationships between two terms as *Typed Dependencies*. These *Typed Dependencies* (see de Marneffe et al. 2006 for further information) are used by our program to identify feature and sentiment candidates in the following.

The extraction of Features and Sentiments was conducted in an iterative process. First, we extracted the most frequent nouns in the corpus, to obtain an initial feature list. The minimum threshold for a noun to become a feature was experimentally decided to be 300 occurrences in the corpus. We also decided to include nouns with a direct grammatical relationship to a possessive pronoun exists into the feature set. The idea was to obtain specific terms that relate to the negotiators' actions and the negotiators' individual characteristics during the course of the negotiation (e.g. "my offer", "your behaviour" etc.). The threshold for these pronoun-noun-combinations was experimentally set to 15 occurrences.

In the next step, we expanded the feature list by synonyms of the extracted words, in order to ensure a certain degree of generalizability from the raining corpus. We used WordNet (Fellbaum 1998) and its Java-Interface JAWS to fulfil this task. However, to obtain meaningful synonym lists from WordNet, the extracted features had to be annotated with their correct word sense. Doing this in an automatic manner is a rather difficult task, and although many heuristics for automatic word sense disambiguation exist (see for example Navigli 2009), the problem itself remains unsolved. Therefore, word senses of the features were distinguished manually.

We then used the feature list to obtain a first collection of sentiment word candidates. For this, we obtained all adjectives and adverbs that were modifying words occurring in our feature list from the corpus. Furthermore, we obtained verbs from the corpus that occurred in negation constructs (such as e.g. “not accept”). The polarity assessment of the sentiment candidates was conducted using two existing sentiment dictionaries, namely those constructed by Hu & Liu (2004) and Wiebe et al. (2005). If a sentiment candidate was found in one of the two dictionaries, its polarity was set accordingly. Conflicts between the two lexica (i.e. a term has a positive polarity in one dictionary and a negative in the other one) were resolved manually.

In the second iteration, the sentiment list created in the first iteration was used to identify rare features, i.e. features that occur rarely in the corpus but in combination with common sentiment expressions. We thus obtained all dependencies between adjectives with a previously identified polarity and nouns (and adverbs and nouns respectively) and added the nouns that had not been in the feature list before.

After the two iterations, we obtained a sentiment lexicon consisting of 726 features and 762 sentiment expressions. A rather similar approach to generate a sentiment lexicon is also presented by Liu (2012). Lastly, the obtained features were manually grouped into one of seven different categories (Feature Generalization similar to Kim and Hovy 2007), in order to generalize the semantic information carried by the features.

The application of the lexicon created in this way will be done according to 3 different evaluation variations:

First, since we used the Stanford Parser to parse the messages, we want to exploit the typed dependencies, i.e. automatically identified direct grammatical relations between single terms in a sentence. Therefore, the first variation evaluates every feature-adjective-dependency where the adjective occurs in the sentiment lexicon according to its polarity. Valence shifting (Kennedy & Inkpen 2006) is performed by using negation relationships, preceding adverbs for intensification and diminishing (e.g. this is a *very* good offer” “your argument is really ridiculous” etc.) as well as adverbial modifiers, again identified via the typed dependencies the adjective occurs in.

The second variation directly operates on the parsing tree, not on the typed dependencies. Sentiment words and feature words are collected on the leaf level and then propagated upwards through the parse tree. Sentiment words are assigned to each feature they meet on a node. Similarly, negating leaves are identified and propagated, modifying the first polar expression they encounter on a node. If no sentiment word is encountered, the sentence is marked as neutral.

The third variation does not rely on parsing relationships and only operates on the part-of-speech-tags assigned to single terms in a sentence. Sentiments and feature words are identified checking each adjective and noun in the sentence. Lastly each feature obtains a polarity score based on the evaluation function given by Liu (2012):

$$score\ (a_i, s) = \sum_{sw_j \in s} \frac{sw_j.so}{dist(sw_j, a_i)}$$

with a_i being the i-th aspect (feature) in sentence s, $sw_j.so$ being the semantic orientation of sentiment word j in s – represented by +1 for a positive polarity and -1 for a negative polarity, and the denominator weighing in the distance of the sentiment word to the feature in the sentence.

In a fourth variation, we also employed a machine learning approach to sentiment classification, this time on sentence granularity. Our collected dataset consists of roughly 25000 single sentences of electronic negotiations. Two human coders subjectively judge those sentences as positive, negative, or as neutral in a negotiation. Based on this set of manually labelled data, we will be training a machine learning model using RapidMiner and its java interface for the application of the model on our experimental data. By comparing different learning models, the most accurate one can be used in the latter classification process. The initial preparation of the data consists of tokenization of the sentences, stemming and lowercasing of the terms used, the generation of uni- and bigrams from the single word tokens, calculation of tf-idf-scores of the respective n-grams and, lastly, a feature selection process based on the information gain criterion, selecting the top 5000 n-grams to generate the final classification model. For detailed information on data preparation and word vector generation steps, see for example Manning et al. (2008).

Table 1 gives a brief summarization of the different variations applied.

Variation	Outline
Typed Dependencies	Exploitation of feature-adjective-relationships identified by the Stanford Parser. Valence shifting via negation relationships Intensification and diminishing of sentiments via adverbs modifying the respective adjective
Stanford Parsing Tree	Propagation of sentiment words along the grammatical parsing tree of the sentence. Sentiment-Feature assignment when a sentiment meets a feature at a node of the tree.
Part-of-speech method	Identification of sentiments and features only by Part-of-speech-tags (i.e. all adjectives and substantives). Polarity scoring via Liu's evaluation function (2012)
Machine Learning	No sentiment lexicon used. Instead, assessment of polar sentences by human coders. ML-Classifier based on this data will label unknown sentences.

Table 1: Overview of the four variations applied

5.0 Conclusion and Outlook

In this paper, we presented our ongoing research on the application of sentiment analysis techniques to mixed-motive communication processes, in our case, electronic negotiations. The contributions during the course of our research in this context encompasses an adaption of a sentiment lexicon for electronic negotiation processes. Furthermore, we seek to contribute to a better understanding of communication processes in electronic negotiations, and how exactly aspects of these communication steps influence the overall result of the negotiation as well as negotiators' assessment and satisfaction with the negotiation. The gained knowledge marks a step towards pro-active communication support in the context of electronic negotiations. A system may use the discussed sentiment analysis techniques in an ongoing negotiation and provide feedback or act as a warning mechanism for the negotiators, when the negotiation is on the brink of failure.

Further steps include the application of the variations to experimental data gathered in an international negotiation experiment in December 2013. We seek to relate the evaluation of our methods to common negotiation outcome variables, the most obvious one being the distinction between successful and failing negotiations. In addition, we seek to focus on efficiency measures such as common substantive-level measurements (Contract imbalance, joint utility (e.g. Tripp and Sondak 1992)), as well as common post-negotiation assessment of the negotiators such as Quality of Communication Experience (Liu et al. 2010) and Process and Outcome satisfaction (Curhan et al. 2006).

A further challenge in the evaluation of the sentiment assessment is the question of aggregation of the sentiment data to message, and finally, negotiation level. This is mostly due to the specific type of interaction, consisting of multiple documents written over time by two different actors. We will have to compare different aggregation dimensions (e.g. all negotiation communication, communication separated by actors, etc.) as well as the exact process of aggregation, and whether the scoring results of the different variations should be integrated to obtain different perspectives on the evaluation of the negotiation process. A separation by aspect categories, as defined earlier can enhance the semantic information of the simple counting of positive/negative statements (e.g. Hu and Liu 2004). Lastly, common phase distinctions of negotiations have to be regarded. While for face-to-face negotiations, different phase models (with differing communicative characteristics) exist (e.g. Olekalns et al. 2003), these structures do not seem to be as prevalent and clear-cut for electronic negotiations (Köszegi et al. 2011).

Lastly, a limitation to be regarded is contextual influence on the negotiation situation, especially from the substantive level, i.e. the general integrativeness of the negotiation situation, power asymmetries, the quality of alternative solutions (BATNAs) – all of which may contribute to a rather strategic usage of negative or positive expressions in a negotiation situation as well as a higher/lowered tolerance by the recipient for such expressions.

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