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WORD FROM THE GUEST EDITORS

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1. THE BACKGROUND

This special issue presents the expanded and improved versions of selected papers from a workshop on Formal and Informal Information Exchange in Negotiations. The workshop took place on May 26–27, 2005, at the University of Ottawa. It was designed to bring together researchers who work on various aspects of interaction in negotiations and those who work in Natural Language Processing or Machine Learning, on problems that might be of interest to negotiation specialists. Such problems include sentiment analysis. Recognizing the sentiments that negotiators express in language (for example, in messages exchanged during electronic negotiations) could offer insight into the negotiation process and a glimpse of the changes in feelings throughout the course of the negotiation. While external factors may influence users at any time, it is likely that they will react fairly consistently to the tone of the partner's messages and offers.

Analysis of texts to recognize attitudes, sentiments, and opinions has been receiving more and more attention in recent years. Hearst (1992) proposed direction-based text interpretation to complement topic analysis. Such interpretation showed where a text lies on the axis from *opposed* to *in favor*. Later work on sentiment analysis abandoned the continuous axis in favor of a binary view: recognize positive and negative (or favorable and unfavorable) attitudes. Most research has an economic motivation, as a result of companies wanting to monitor the consumers' satisfaction with their products (Cognitrend,[1] Tenorio Research).[2] Opinion recognition may also increase the usefulness of search engines by allowing the user to compare the number and content of positive and negative opinions about a variety of products and services (Das and Chen 2001; Dave, Lawrence, and Pennock 2003; Hu and Liu 2004) or as part of recommender systems which collect, analyze, and summarize user opinions (Tarveen et al. 1997; Mooney, Bennet, and Roy 1998; Tatemura 2000).

Hearst (1992) and Sack (1994) propose cognitively inspired models for sentiment analysis. Hearst's model is inspired by Talmy's theory of force dynamics (Talmy 1985), which describes the lexical and grammatical expressions of the interaction between two opposing entities—the agonist and the antagonist. Each entity expresses an intrinsic force, tending either toward motion or toward rest. The balance between these forces determines the resulting state of the interaction. In a variation on this idea, the focus is on one entity and on the events that affect it during encounters with other entities. This can be imagined as an entity following a path toward a goal or destination, and meeting barriers or facilitators along the way. This *path model* is what Hearst applies, with minor modifications, to queries that have a directional component, which imply finding whether an agent or event opposes or is in favor of another event. Sack briefly describes *SpinDoctor*, a system designed to identify the point

[1] http://www.cognitrend.com
[2] http://tenorioresearch.itgo.com

of view of a news report. Despite having to be objective reports of facts, news reports are often biased, although sometimes not consciously. Sack's system builds on the observation that news writers are consistent in the attributes they bestow upon the actors involved in news. In order to identify the point of view of a news story, the system uses heuristics and a database of "fairy-tale-like roles," which American journalists used to describe events and participants in the first Gulf War (Lakoff 1991).

Das and Chen (2001) analyze the opinions of small investors about the stock market, through messages from Yahoo!'s message board. Processing the messages downloaded from the message board involves the use of a generic English dictionary (CUOVALD), and a manually built collection of specific financial terms that manual analysis has shown to be relevant to this task. Statistical techniques help select the most discriminating words over the training data. For a specific stock, several algorithms would help suggest whether the investors' opinion is to buy or sell, or whether it is neutral.

Currently, sentiment analysis is approached mostly as a text-classification problem. A textual unit of certain size is classified as expressing positive or negative (or favorable and unfavorable) feelings. The unit size can go from words (Hatzivassiloglou and McKeown 1997; Hatzivassiloglou and Wiebe 2000; Wiebe 2000; Turney and Littman 2003) to full texts (of various size), starting with a small set of seed words (Turney 2002; Pang, Lee, and Vaithyanathan 2002; Pang and Lee 2004), manually built lexicons (Subasic and Huettner 2001; Das and Chen 2001), a mixture of unigrams, word sentiment measure, topic knowledge (Mullen and Collier 2004), or even the world knowledge captured in the Open Mind Commonsense database (Liu, Lieberman, and Selker 2003).

Another way of analyzing sentiment is to identify smaller text units, which convey feelings and features that indicate subjective language (Wiebe 1990; Hatzivassiloglou and Wiebe 2000; Wiebe 2000; Wilson, Wiebe, and Hwa 2004). It is known that a text, especially longer text, may express various opinions on various aspects of a product or a service. It is therefore important to separate objective from subjective text units, and proceed with sentiment analysis of the subjective parts (Pang and Lee 2004).

Sentiment analysis is an interesting field, and research in the area grows and diversifies, as shown also in the collection (Qu, Shanahan, and Wiebe 2004). This special issue also contributes to the field. The four papers look at four different questions in the area of sentiment analysis: how to recognize the strength of opinions presented in texts; how important neutral examples are in classifying positive and negative examples; how valence shifters influence the sentiments expressed in a text unit; and finally, what makes us laugh.

2. THE PAPERS

In accordance with the organization of the Ottawa workshop, the issue opens with a paper on recognizing the strength of opinion clauses in text. Wilson, Wiebe, and Hwa continue their work on subjectivity/objectivity analysis by taking their endeavor one step further (Wilson et al. 2004). Identifying strong and weak opinion clauses will allow both people and automated systems to follow the evolution of feelings toward issues, products, or services. More and more often, such opinions appear on the Web in blogs, news reports, messages posted on electronic boards, and so on.

Koppel and Schler address an important, and thus far underappreciated, issue in Machine Learning related to sentiment analysis. It seems customary to focus on classifying sentiment using positive and negative examples (Pang et al. 2002; Turney 2002; Turney and Littman 2003). There may be an implicit assumption that units which do not express feelings are irrelevant to this type of learning. Research on classification finer-grained than just positive–negative does not explicitly consider neutral examples—the approach is to compute a metric that combines label similarity with sentiment analysis to arrive at a label assignment (Pang and Lee 2005). Koppel and Schler show that using neutral examples leads to significant improvements in learning to distinguish positive and negative examples.

Positive and negative sentiment analysis often relies on such indicators as seed words—nouns, verbs, and adjectives—with a semantic orientation that people agree upon. A word's semantic orientation may diminish or even change because of so-called *valence shifters*. In the task of automatically classifying reviews as positive or negative, Kennedy and Inkpen explore three types of valence shifters: negations (they reverse the polarity of a term), intensifiers, and diminishers (they affect the degree to which a term is positive or negative).

The special issue concludes on a cheerful note, with an excursion into computational humor. In more typical sentiment analysis tasks, feelings are captured in words on whose orientation people tend to agree. While a joke also relies on words to elicit a positive feeling, there is seldom one crucial funny word. We see word play, or a seemingly serious reference made amusing in context, and so on. It is not easy to identify word combinations that bring about a humorous effect. Mihalcea and Strapparava explore one-liner jokes and find out what makes them funny by comparing them with similarly worded serious sentences and equally serious proverbs.

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