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Sentiment Analysis from Opinion Mining to Human-Agent Interaction

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Abstract: The opinion mining and human-agent interaction communities are currently addressing sentiment analysis from different perspectives that comprise, on the one hand, disparate sentiment-related phenomena and computational representations, and on the other hand, different detection and dialog management methods. Sentiment/opinion detection methods used in human-agent interaction are indeed rare and, when they are employed, they are not different from the ones used in opinion mining and consequently not designed for socio-affective interactions to support our claims, we present a comparative state of the art which analyzes the sentiment-related phenomena and the sentiment detection methods used in both communities and makes an overview of the goals of socio-affective human-agent strategies. Sentiment analysis for human-agent interactions in two different use cases: job interviews and dialogs with museum visitors.

Keywords: Opinion mining, sentiment analysis, Human-agent interaction.

I. INTRODUCTION

The domain of sentiment analysis has seen an upsurge of interest with the rapid increase of available text data containing opinions, critics and recommendations on the web (movie reviews, forum debates, tweets and other entries in social networks). A challenging area is the development of opinion detection methods relying on these new sources. Opinion detection systems using sentiment analysis have been developed to target customers and evaluate the success of marketing campaigns , to know the user experience with certain products or their image of brands, or to predict stock price fluctuations. Another growing research field is the development of embodied conversational agents (ECAs), virtual characters able to interact with humans. ECAs are involved in various applications. A variety of work addressing the aspects of emotion modeling can be found. Particularly paradigmatic and prolific are the studies by Scherer and colleagues presenting surveys on different aspects of defining, producing and modeling emotion. Notably, the work by Schuller and Batliner, who have organized special issues, challenges and a book in the topics of paralinguistic in speech and language and emotion in interaction. The context of this work is the development of a sentiment analysis module and its integration in an ECA platform dealing with multimodal socio-emotional interactions.. The verbal content analysis will be correlated to acoustic and video analysis of user's socio-emotional behaviors. The final goal is thus to determine which reaction an ECA should have according to the user's detected socio-emotional. Sentiments, opinions, judgments, appreciations, textual affect, each of these words refer to phenomena which present both specific features and overlaps. The related linguistic cues are strongly dependent to the chosen definition. Sentiment analysis in text relies on various theoretical frameworks, coming in a major part from two research communities: the psychology and the linguistics.. In particular, we want to investigate sentiment analysis both as a cue for interpersonal engagement and as a cue for user's socio-emotional behavior analysis.

II.LITERATURE REVIEW

Chloe Clavel et al [1]. Demonstrated on identify and discuss the growing opportunities for cross-disciplinary work that may increase individual advances. Sentiment/opinion detection methods used in human-agent interaction are indeed rare and, when they are employed, they are not different from the ones used in opinion mining and consequently not designed for socio-affective interactions (timing constraint of the interaction, sentiment analysis as an input and an output of interaction strategies). sentiment analysis for human-agent interactions in two different use cases: job interviews and dialogs with museum visitors. various avenues for the integration of sentiment analysis in face-to-face human-agent interactions

Björn Schuller et al [2]. Described mainly involve two areas, namely research with human participants, and protection of personal data. Some other ethical issues coming with such data such as its exploitation in real-life recognition engines and evaluation in long-term usages are, however, less explored. Here, we aim to discuss both – the more "routine" aspects as well as the white spots in the literature of the field.

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Vinodhini G et al [3]. There are few different problems predominating in this research community, namely, sentiment classification, feature based classification and handling negations. From the above work it is evident that neither classification model consistently outperforms the other, different types of features have distinct distributions.
I R Jayasekara et al [4]. Described Automating the opinion mining process was identified as a solution for the problem. Although there are algorithms for opinion mining, an algorithm with better accuracy is needed. A feature and smiley based algorithm was developed which extracts product features from reviews based on feature frequency and generates an opinion summary based on product features.

III. PROPOSED WORK

In this System used to analysis the sentiment of human agent interaction, sentiment analysis is focused on the classification of positive/negative valence, and affect analysis or emotion recognition in recognizing more fine-grained emotions. The dimensional approach, from psychology, is the most frequently used, even though it is barely mentioned explicitly most detection systems focus on the value axis and a polarity analysis consisting of a positive vs negative detection. Agent analysis the feelings and emotions of human and the interactions based on sentiment analysis.

IV. METHODOLOGY

A. Overview of sentiment theoretical models from ECA's point of view

Sentiments, opinions, judgments, appreciations, textual affect, each of these words refer to phenomena which present both specific features and overlaps. The related linguistic cues are strongly dependent to the chosen definition. One of the key task of sentiment analysis is therefore to understand the underlying theories of each phenomena, and how relevant they are according to the application and to the studied databases.

B. The dimensional axes

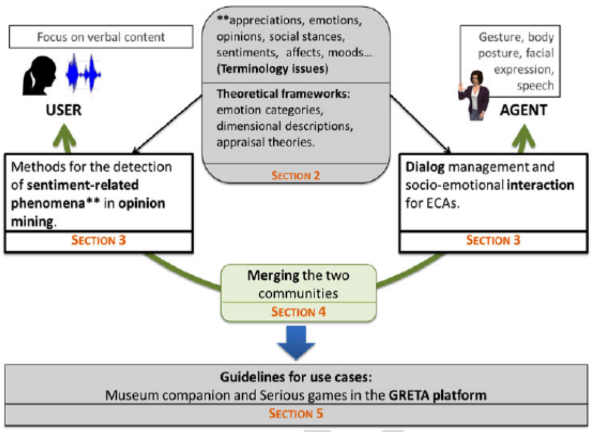
The psychological model from Osgood is the most frequently used by detection systems. Indeed, the major part of detection systems focus on one of the axes defined in the Osgood theory, the valence axis, and propose a positive vs. negative classification. However, from an ECA's point of view, dimensional axes such as valence and arousal should not be used alone, because we think that this model can prevent from modeling the complexity of sentiment phenomena.

C. Terminologies

Sentiments, opinions, emotions, moods, appreciations, social stances. Scherer defines the term emotion and its specificity according to other phenomena: preferences, attitudes, affective dispositions, and interpersonal stances. These definitions are references in the affective computing community. The natural language processing (NLP) community tends to use more frequently opinion and sentiment, whereas the ECA community tends to use emotions, but the actual studied phenomena overlap.

D. Opinion Mining Perspective

Affects, emotions, sentiments, opinions: distinguish affect (or emotion) and sentiment analysis as two different research areas closely related to recognition. The authors state that sentiment analysis is focused on the classification of positive/negative valence, and affect analysis or emotion recognition in recognizing more fine-grained emotions. Many authors are consistent with this classification, even though they sometimes concede that the distinction between affect and sentiment is not clear in the community.



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E. ECAs Perspective

The Emotion Markup Language (EmotionML) from the W3C2 specifies the various terminologies and theoretical models that have to be used for both the automatic recognition of emotion-related states from user behavior and the generation of emotion-related system behavior.

F. Frameworks of Sentimentrelated Phenomena

We propose here a common categorization of these frameworks that arise from both communities: dimensional (representation of sentiment-related phenomena on different axes, such as valence and arousal discrete (representation of sentiment-related phenomena into distinct categories, such as fear or joy and appraisal (sentiment-related phenomena are linked to the process of evaluation of events, objects or persons

a. Opinion Mining Perspective

Although the underlying theoretical frameworks of the opinion mining and sentiment analysis are not always clear, there exists some background literature in this domain which comes from three main research communities: psychology, sociology and linguistics. The dimensional approach, from psychology, is the most frequently used, even though it is barely mentioned explicitly.

b. ECAs Perspective

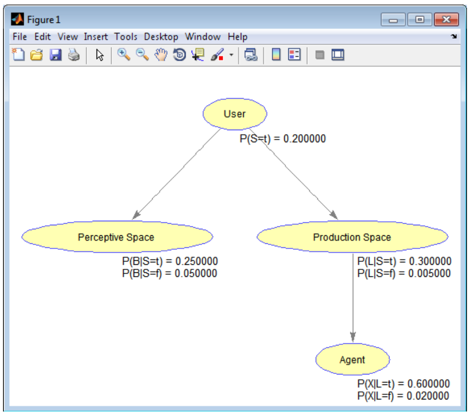
The ECA community essentially relies on the field of psychology to build its model for expressing emotional behaviors and interacting with humans, with a focus on the detection of emotion from speech or from visual cues (facial expressions, gesture, posture).

V. EXPERIMENTAL RESULTS

A. Overview of computational methods for sentiment analysis

The computational sentiment analysis is carried out in the literature through two types of methods: methods based on semantic rules and statistical methods. The first one concerns the design of rules for the extraction and automatic labeling of sentiment related expressions contained in texts. It relies on sentiment lexicons such as linguistic extraction patterns combining different features obtained from the morpho-syntactic analysis (word form, lemma, part of speech tags) or from outputs detected by other rules. The second one are based not only on simple methods such as word counts but also on machine learning methods.

Existing sentiment analysis systems still hardly deal with some sentiment specific issues. Indeed, the challenge for existing sentiment analysis systems – and for methods based on semantic rules, in particular – is to deal with complex natural language processing issues such as the processing of the negation and of the intensifiers, anaphora resolving to link the evaluation to its target and its source, the use of metaphors to express sentiment, the integration of the context to disambiguate the detected opinion sense (e.g. personality, social or political affiliations of the speaker).



The trend to handle these issues is the development of hybrid methods, relying both on the generalization capabilities of machine-learning approaches and the in-depth modeling offered by methods based on semantic rules, which uses probabilistic model for disambiguisation.

As explained in the previous section, another key challenge for the sentiment analysis task is to go beyond the positive vs. negative classes – that is the definition of the relevant sentiment classes or concepts to be detected. All the theoretical models shows all the complexity of the sentiment or evaluation-related phenomenons, which is not always adequately addressed in the computational models developed for sentiment detection. The majority of computational

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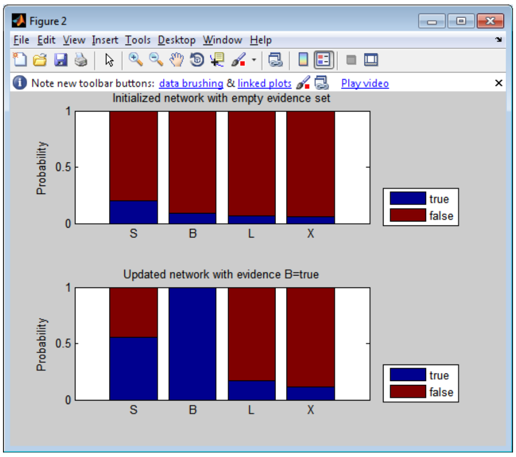
methods focus on the positive/negative distinction or intensity axis. Other works focusing on basic emotion categories can be found and even scarcer are the works distinguishing the affect to judgment and relying the sentiment to its target.



The results of sentiment analysis systems are worst than for other natural language processing classification tasks. Whatever the scores are, it is important to keep in mind that the performance of such systems is strongly dependent to: the type of the data to be analyzed: the style and the language register of the writer/speaker, the quality of the syntactic structure of the data (tweets and oral transcription vs. journal paper) the classes of sentiment that are considered: classification according to 10 classes is indeed more difficult than for two classes. Performance also depends on the choice of classes being studied, e.g. discriminating between appreciation and judgment is generally more difficult than between positive and negative. The quality of the ground-truth annotations: evaluating performance in classification and recognition systems consists of analyzing differences between ground truth annotations and the system decisions. In the field of emotions and sentiments, we cannot speak about actual human error, since the situation is far more complex. The sentiment text content annotation is subject to subjectivity and it is therefore difficult to merge different annotations. As a result, performance is dependent on reference annotations.

B. Towards a sentiment detection system for human-agent face-to-face interaction

a. Oral adaptation of computational methods

The targeted human-agent interaction is face-to-face, which means that verbal content takes place in a context of a multimodal speech. Given this context, a first step towards multimodality is to consider sentiment analysis from the speech signal point of view. The speech signal provides complementary information to the linguistic content for sentiment analysis through acoustic features such as prosody, voice quality or spectral features which are relevant to characterize the affective component of sentiment. Above all, acoustic features are crucial to characterize paralinguistic features such as laugh. Besides, the linguistic-based sentiment analysis methods developed on oral data have to deal with speech variability: the inter-speaker and intra-speaker variability (emotion, speaking style, linguistic variations, poor grammatical construction, badly pronounced words etc.). This variability causes two issues for oral data analysis, scarcely addressed in the context of sentiment analysis : the errors engendered by the ASR (Automatic Speech Recognition) systems, whose performances strongly depend on the background noise and the quality of the recording

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system; the spontaneous speech features contained in the user utterance. Even correctly transcribed, spontaneous speech features such as disfluencies, backchannels and overlapping speech introduce some noise in the text from a text based detection system point of view. Indeed, the presence of disuency phenomena (e.g. repetitions, hesitations, etc.) disrupts the syntactical structure of the message.

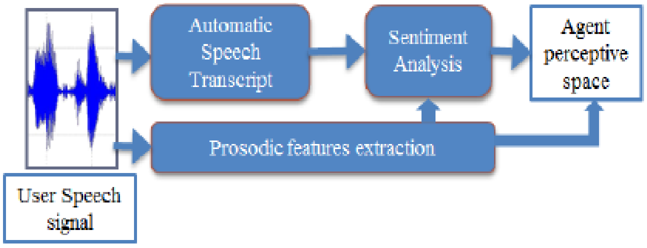
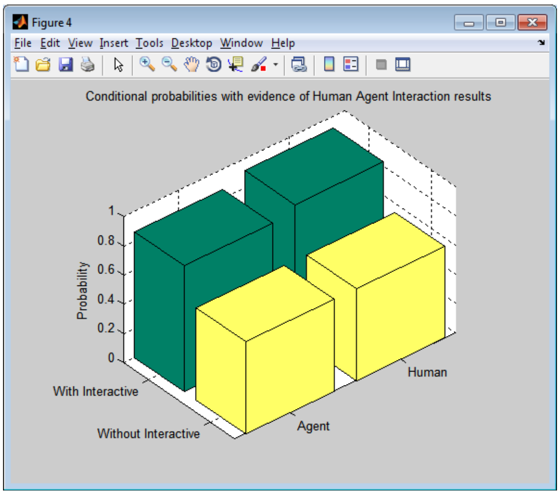


Figure 1 presents the framework that we want to propose

For our sentiment analysis module designed to integrate the non verbal component of speech. The linguistic-based sentiment analysis will be carried out on automatic speech transcripts, addressing the two previously described issues: ASR errors and spontaneous speech features. For the ASR errors, the confidence score and the various hypothesis of the ASR outputs have to be taken into account. For the spontaneous speech features, we want to integrate disfluencies in our model. Indeed, disfluencies can also have a strategic function in the conversation. Disfluencies can also be linked to the speaker emotional states.
Even though the main analysis will concern the linguistic content, our system proposes to rely on the combination of the linguistic features and the prosodic features. This combination will be considered on the one hand by aligning the transcription with the extracted prosodic features in order to build multimodal sentiment model. On the other hand, prosodic features extraction will be considered independently to the linguistic content in order to define quick interaction strategies from the detected acoustic manifestation of emotional state.



b. Processing time and decision frame of sentiment analysis

The processing time of sentiment analysis is not a crucial issue in the context of large database analysis and is not adequately addressed in the literature. However this issue plays a major role when considered in an interaction. A relevant answer to user sentiment in-depth analysis but which occurs too late in the interaction is not conceivable.
The existing real-time linguistic-based sentiment analysis methods such as [23] are based on keywords spotting and on methods based on simple semantic rules. The processing time of such methods strongly depends to both the device on which the ECA is developed and the complexity of the methods. In particular, in the case of oral data processing, methods relying on keyword spotting from speech signal (without relying on an enriched automatic transcription) have a lower processing time than methods relying on complex semantic rules or on machine learning methods using a complex representation of textual features.
Another point related to reaction time of the ECA is the decision frame used for sentiment analysis. Indeed, the sentiment analysis issue can be expressed in two ways: the classification of text utterances or the assigning of sentiment linked expressions to sentiment concepts. In both cases, the units of the text utterance from which the system takes the decision have to be defined: the clause, the sentence, speaker turn segments, the speaker turn.

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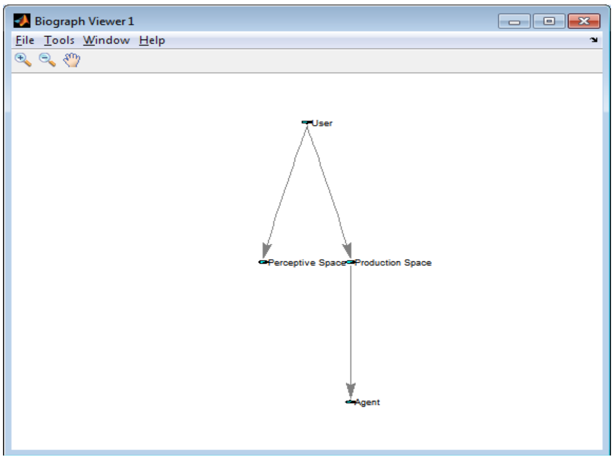


C. Sentiment analysis and interaction strategies – prospects

We present in this section some tracks related to the development of interaction strategies linked to the sentiment analysis module in an ECA platform. The first subsection presents the targeted ECA platform and the second one presents the tracks that are envisaged concerning the interaction strategies that are built on this architecture.

a. The targeted human-agent architecture

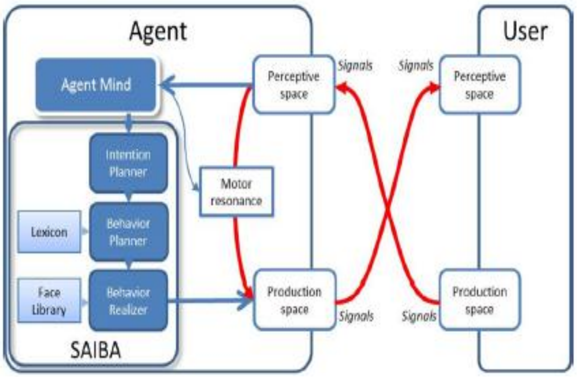
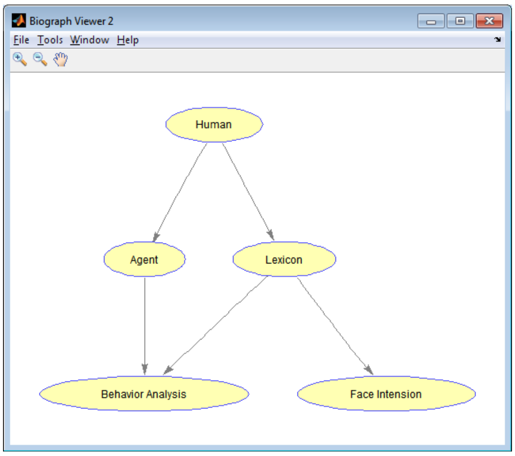


Figure 2 presents the global architecture of an ECA platform, as imagined for the ECAs from Greta.

The SAIBA architecture (an international common multimodal behavior generation framework) is here increased by the cognitive reasoning of the agent and the interaction with the user through two modules:
_ The Agent Mind includes both a representation of agent's cognitive and socio-emotional states (its emotions, its social relationships, its goals and beliefs) and reasoning models allowing one to compute and update these features along the interaction. This module provides the communicative intentions of the agent.



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_ The Motor resonance manages the direct influence of the socio-emotional behaviors of the user (agent perceptive space) to the ones of the agent (agent production space) without cognitive reasoning. In particular, the resonance motor allows the ECA to align its behavior on the user's behavior, for example by mimetism.

VI. CONCLUSION

The work proposes various research tracks for the integration of sentiment analysis in a face-to-face human-agent interactions. The challenges implied to reach this aim are numerous and cross-disciplinary. First, we have to rely on psycho-linguistic models in order to define the sentiment-related phenomena that are interesting to be considered by an ECA. Second we have to develop hybrid methods relying both on the development of semantic rules and on machine learning methods in order to integrate the various levels of complexity of sentiment-related phenomena. Finally the literature on human-computer interaction have to be called up in order to develop interaction models for the processing of sentiment analysis by a socio-emotional ECA. we introduce a SA method embedded in a ECA system and which deals with the human-agent interaction issues. In this way, we delimit the relevant sentiment-related phenomenon according the agent's communicational goals and make a connection between the liking dimension and the model of attitude provided. Then, we introduce the ability of our system to deal with the conversational context by modeling agent's utterances for the detection of user's expressions of likes and dislikes. The system is next evaluated by a protocol integrating conversational issues and which relies on a non-expert and system-oriented annotation task. The in-depth analysis of the agreement and disagreement between the system and the reference provides some tracks for the improvement of the system and a better adaptation to the agent communicational goals: a distinction of implicit and explicit expressions of likes and dislikes, an integration of a larger conversational context and a management of the speech disfluencies.

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