



Challenges and Methods for opinion analysis in interactions

from human-human to human-agent interaction

Chloé Clavel, Associate Professor in Affective Computing September 4, 2017

LTCI, Telecom-ParisTech

Telecom-ParisTech, Social Computing Topic

LTCI (Information and Communications Laboratory) : research laboratory of Telecom ParisTech

Collaborators within the Social Computing Topic

- 10 professors working on machine learning, signal processing, sociology for social computing¹
- 3 Contract-funded Researchers
- 5 phd students

¹https://www.tsi.telecom-paristech.fr/recherche/themes-de-recherche/ analyse-automatique-des-donnees-sociales-social-computing/

Telecom-ParisTech, Social Computing Topic

Social Computing research topics

- Social web analysis
- Multimodal social signal processing
- Human-agent interaction

European and national projects of the team

- Chaire Machine Learning for Big Data
- Labex SMART
- European projects : Aria-Valuspa, Animatas (PhD open positions available http://animatas.isir.upmc.fr/index.php?perma=Positions)

Human-agent subtopic : the greta-team

The greta team conducted by Catherine Pelachaud (ISIR)²



²http://www.tsi.telecom-paristech.fr/mm/en/themes-2/greta-team/

Some references to the human-agent research work

Overview on the work on human-agent interaction

Clavel, C., Cafaro, A., Campano, S., & Pelachaud, C. (2016). Fostering user engagement in face-to-face human-agent interactions: a survey. In Toward Robotic Socially Believable Behaving Systems-Volume II (pp. 93-120). Springer International Publishing.

Human-robot interaction database for user engagement studies

Atef Ben Youssef, Miriam Bilac, Slim Essid, Chlo Clavel, Angelica Lim, Marine Chamoux, UE-HRI: A New Dataset for the Study of User Engagement in Spontaneous Human-Robot Interactions In Proceedings of ACM International Conference on Multimodal Interaction, Glasgow, Scotland, November 2017 (ICMI17)

Some references to the human-agent research work

Use of speech (verbal and prosody) content for social computing in human-agent interaction

Alignment strategies on user utterance

S. Campano, C. Clavel, C. Pelachaud, *I like this painting too : when an ECA shares appreciations to engage users*, in AAMAS 2015

Dubuisson Duplessis, G.; Clavel, C.; Landragin, F., Automatic Measures to Characterise Verbal Alignment in Human-Agent Interaction, 18th Annual Meeting of the Special Interest Group on Discourse and Dialogue (SIGDIAL), 2017

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• Generation of socio-emotional behavior

Janssoone, T., Clavel, C., Bailly, K. and Richard, G. Using temporal association rules for the synthesis of embodied conversational agents with a specific stance. IVA 2016

Outline of the talk

Challenges and Methods for Opinion Analysis in Interactions

- 1. Social context and applications of opinion analysis
- 2. Terminology and theoretical models
- 3. Opinion detection methods in interactions
- 4. Perspectives of opinion analysis

Social context and applications

Opinion analysis and social data Opinion analysis and Human-agent/robot interaction

Opinion analysis and social data

Social data

Expressions of the citizens on the web [Cardon, 2013]



Opinion analysis and social data Opinion analysis and Human-agent/robot interaction

Opinion analysis and social data

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Applications

- Sociology : social trends analysis, elections, etc.
- Recommendation : review analysis (movies, music, books)
- Marketing : e-reputation, impact of a communication campaign



Opinion analysis and social data Opinion analysis and Human-agent/robot interaction

Opinion analysis and Human-agent/robot interaction

Opinion analysis and virtual advisor for the management of customer relationship



Social context and applications

Terminology and Theoretical models Opinion detection methods in interactions Perspectives of opinion analysis

Opinion analysis and social data Opinion analysis and Human-agent/robot interaction

Human-agent/robot interaction

Personalized virtual assistant



Social Robotics



Terminology and Theoretical models

Terminology

Sentiment/opinion-related phenomena

Emotion, opinion, sentiment, mood, attitude, interpersonal stance, personality traits, affect, judgment, appreciation, argumentation, engagement

Terminology and opinion phenomena

Modalities of expression

Verbal content, prosody, Gesture, Posture, Facial expressions, physiological signal





Figure 1: O Sentimental Machine de William Kentridge

Terminology

Terminology and opinion phenomena Theoretical models

Scherer's definitions [Scherer, 2005]

Emotion: short phenomenon, physiological reaction, appraisal of a major event (stimulus)

 $\textbf{Mood:} \ \text{diffuse non-caused low-intensity long-duration change in subjective feeling}$

Interpersonal stances: affective stance toward another person in a specific interaction

Attitudes: enduring, affectively colored beliefs, dispositions towards objects or persons

Personality traits: stable personality dispositions and typical behavior tendencies

Exercise : link the following terms to the most relevant phenomenon liking, gloomy, contemptuous, jealous, sad

Terminology and opinion phenomena Theoretical models

Terminology and applications

Challenges: choose the relevant phenomenon according to the application and the data [Clavel and Callejas, 2016]

Examples

Detect when the student is frustrated or bored in e-learning system \Rightarrow emotion

Detect depressed persons at home in robot companion systems \Rightarrow mood

Detect extrovert personality in job interview data \Rightarrow personality traits

Clavel, C.; Callejas, Z., *Sentiment analysis: from opinion mining to human-agent interaction*, IEEE Transactions on Affective Computing,(2016)

Terminology and opinion phenomena Theoretical models

Theoretical models used in language

Use theoretical models to delimit the linguistic phenomenon of opinion

 \hookrightarrow Example : Appraisal theory from systemic functional linguistics [Martin and White, 2005]

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An appraisal expression is a **source** that **evaluates** a **target** \Rightarrow 3 components.

don't like

source = user				
target = Dali				
polarity = neg				

Advantage:

- Identify the opinion target
- Distinguish the evaluative stances : Affect (personal reaction referring to an emotional state) to Judgment (assigning qualities - e.g. tenacity - to individuals according to normative principles) and Appreciation (Evaluation of an object e.g. a product or a process)

Standardization

Terminology and opinion phenomena Theoretical models

Emotion : Emotion Markup Language http://www.w3.org/TR/2014/REC-emotionml-20140522/

Opinion and sentiments http://www.w3.org/community/sentiment/ : Linked Data Models for Emotion and Sentiment Analysis Community Group

Opinion detection methods in interactions

General challenges

Scientific challenges

Knowledge-based methods for opinion analysis Machine learning for opinion dynamics modelling in in-the-wild corpora System evaluation

Exercise : Positive or negative ?

What is the opinion of the speaker about the movie? Positive? Negative?

Identify the words corresponding to the expression of an opinion. Are they positive or negative?

This film should be brilliant. It sounds like a great plot, the actors are first grade, and the supporting cast is good as well, and Stallone is attempting to deliver a good performance. However, it cant hold up.

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- \hookrightarrow more complex than a simple positive vs. negative word counts.
 - conditional tense
 - discourse markers
 - negation processing (I don't like this movie)
 - modifiers and intensifiers (the plot is not very good)
 - dealing with metaphors (global warming vs. climate change [Ahmad et al., 2011])

First challenge : noisy data

Scientific challenges

Knowledge-based methods for opinion analysis Machine learning for opinion dynamics modelling in in-the-wild corpora System evaluation

How to deal with in-the-wild data?

 \hookrightarrow in real applications, corpora are wild [Schuller et al., 2016] and contain spontaneous conversational data

First challenge : noisy data

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Example : transcripts of call-centre data and disfluencies

Disfluences combinées Vous regardez les 5 derniers **chiffres** des **chi** des numéros gravés, pas les chiffres qui défilent **hein**

First challenge : noisy data

Scientific challenges

Knowledge-based methods for opinion analysis Machine learning for opinion dynamics modelling in in-the-wild corpora System evaluation

How to deal with in-the-wild data?

Linguistic modelling of spontaneous opinion expressions including

- oral and interactional features (ex: disfluencies)
- written features (ex : typos, chat features: lol, A +, mouhahaha)

C. Clavel, G. Adda, F. Cailliau, M. Garnier-Rizet, A. Cavet, G. Chapuis, S. Courcinous, C. Danesi, A. Daquo, M. Deldossi, et al. *Spontaneous speech and opinion detection: mining call-centre transcripts.* Language Resources an Evaluation, 2013.

Scientific challenges

Knowledge-based methods for opinion analysis Machine learning for opinion dynamics modelling in in-the-wild corpora System evaluation

Second challenge : opinion dynamics





Scientific challenges

Knowledge-based methods for opinion analysis Machine learning for opinion dynamics modelling in in-the-wild corpora System evaluation

Second challenge : opinion dynamics



Scientific challenges

Knowledge-based methods for opinion analysis Machine learning for opinion dynamics modelling in in-the-wild corpora System evaluation

Third challenge : human-agent interactions



Clavel, C.; Callejas, Z., *Sentiment analysis: from opinion mining to human-agent interaction*, IEEE Transactions on Affective Computing,(2016)

Scientific challenges

Knowledge-based methods for opinion analysis Machine learning for opinion dynamics modelling in in-the-wild corpora System evaluation

Third challenge : human-agent interactions



Features of human-agent interaction

• User's expression of opinion depends on agent's utterance

Scientific challenges

Knowledge-based methods for opinion analysis Machine learning for opinion dynamics modelling in in-the-wild corpora System evaluation

Third challenge : human-agent interactions



Features of human-agent interaction

- User's expression of opinion depends on agent's utterance
- the agent has its own social strategy
 - \hookrightarrow delimit relevant opinions according to agent's social goals

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Knowledge-based methods : general principles

Lexicons

- Sentiment lexicons (ex : Sentiwordnet, wordnet Affect [Strapparava and Valitutti, 2004], LIWC)
- Domain lexicons (ex : Wordnet Domain)

Extraction rules

- negation, intensifiers processing [Taboaba et al.]
- Compositional approaches [Moilanen 2007]
- Bottom-up rule-based approach [Langlet and Clavel, 2015]

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Knowledge-based methods : extraction patterns

Example : bottom-up rule-based approach based on three levels of the utterance



C. Langlet and C. Clavel, Improving social relationships in face-to-face human-agent interactions: when the agent wants to know users likes and dislikes, in ACL 2015

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Knowledge-based methods for opinion analysis in human-agent interactions

 $\ensuremath{\mathsf{Extraction}}$ patterns and semantic rules in order to integrate the human-agent interaction context



 \hookrightarrow rules at the adjacency pair level (agent utterance, user utterance)

C. Langlet and C. Clavel, Improving social relationships in face-to-face human-agent interactions: when the agent wants to know users likes and dislikes , in ACL 2015

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Knowledge-based methods for opinion analysis in human-agent interactions

Use dialog structure and history in order to help analysis of opinion target *I like it*

- → use the topic structure of the scenario to help the modelling of the potential opinion target
- \hookrightarrow Link the opinion target to the topic

Caroline Langlet, Chloe Clavel, Grounding the detection of the users likes and dislikes on the topic structure of human-agent interactions, Knowledge-Based Systems (2016)

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Machine learning : general principles

Two tasks :

- classification of documents in opinion categories (ex : positive/negative) using supervised machine learning approaches : SVM (Support Vector Machine), Naive bayes classifier (see Lab Wednesday), deep learning approaches
- sequential annotation of opinion, source and target using sequential approaches (ex: Conditional Random Fields, recurrent neural networks)

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I_DSE	I_DSE	I_DSE	I_DSE	I_DSE	0

Figure 2: from (Irsoi and Cardie)

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Machine learning vs. knowledge-based

ML advantages

- few linguistic expertise is required to build the model from the annotated data,
- a higher interoperability of the models

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Machine learning vs. knowledge-based

ML advantages

- few linguistic expertise is required to build the model from the annotated data,
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ML drawback

- require a labelled dataset (big dataset for deep learning approaches) while annotating data in opinions is a difficult task
- difficult interpretation of trained models
- difficult to transfer model on different data (the model is corpus-dependent)

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Textual Features : general principles

Classic representation : bag of words/ Ngrams

Figure 3: From Miha Grcar Text mining and Text stream mining tutorial



- the word order in the sentence is not modelled
- Ex: these two sentences are represented by the same vector : Mary is quicker than John and John is quicker than Mary

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Textual Features : general principles

Word embeddings (ex : word2vec)



- learned representations : representation of the words in semantic vectors, capture the semantic links between words using their occurrence context
- the vectors are trained on textual dataset using neural network approaches (see Mikolov, Tomas, et al. "Distributed representations of words and phrases and their compositionality." Advances in neural information processing systems. 2013.)
- pretrained vectors available from Google https://code.google.com/p/word2vec/

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Machine learning for opinion dynamics modelling



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Machine learning for opinion dynamics modelling

Example of study

Model dynamics of movie review by using HCRF (Hidden Conditional Random Field) a latent state model interpretable and efficient with a small dataset

Barriere, V., Clavel, C., Essid, E., Opinion Dynamics Modeling for Movie Review Transcripts Classification with Hidden Conditional Random Fields, Interspeech 2017

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HCRF for modelling opinion dynamics



Barriere, V., Clavel, C., Essid, E., Opinion Dynamics Modeling for Movie Review Transcripts Classification with Hidden Conditional Random Fields, Interspeech 2017

System evaluation

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How to evaluate the opinion analysis system ?

Build a reference to compare with algorithm output : difficulty of the annotation task, use crowdsourcing annotation platform

Evaluation measures : Accuracy, F-score, precision, recall , kappa...

C. Langlet and C. Clavel, Adapting sentiment analysis to face-to-face human-agent interactions: from detection to evaluation issues, in ACII 2015

Perspectives of opinion analysis

In a nutshell Guidelines

In a nutshell

A pluridisciplinary topic

Linguistics, psychology, sociology, natural language processing, machine learning, knowledge modelling

- ex: [Langlet and Clavel, 2015] knowledge-based approach to model opinions
- \hookrightarrow opinions as defined by the appraisal theory
- \hookrightarrow appraisal theory derived from functional systemic linguistics

In a nutshel Guidelines

Big data and machine learning for opinion analysis

Difficulty to obtain big data labelled in opinions

 \hookrightarrow opinions are phenomena that are complex to annotate

Guidelines :

- \hookrightarrow take advantage of crowdsourcing platforms in order to collect massive annotations
- \hookrightarrow use semi-supervised approaches, active learning and transfer learning
- → use hybrid approaches on smaller datasets such as done for opinion detection in [Lavalley et al., 2010b], disfluency detection in [Dutrey et al., 2014]
- ↔ work on in-the-wild data to obtain relevant and robust opinion models [Dutrey et al., 2014, Clavel et al., 2013]

Key references on opinion analysis

- [Clavel and Callejas, 2016] Clavel, C.; Callejas, Z., *Sentiment analysis: from opinion mining to human-agent interaction*, IEEE Transactions on Affective Computing,(2016)
- [Langlet and Clavel, 2016] Caroline Langlet, Chloe Clavel, *Grounding the detection of the users likes and dislikes on the topic structure of human-agent interactions*, Knowledge-Based Systems (2016)
- [Barriere et al., 2017] Barriere, V., Clavel, C., Essid, E., Opinion Dynamics Modeling for Movie Review Transcripts Classification with Hidden Conditional Random Fields, Interspeech 2017
- [Clavel et al., 2013] C. Clavel, G. Adda, F. Cailliau, M. Garnier-Rizet, A. Cavet, G. Chapuis, S. Courcinous, C. Danesi, A. Daquo, M. Deldossi, et al. Spontaneous speech and opinion detection: mining call-centre transcripts. Language Resources an Evaluation, 2013.
- [Lavalley et al., 2010a] R. Lavalley, C. Clavel, M. El-Bze, and P. Bellot. *Finding topic specific strings in text categorization and opinion mining contexts.* DMIN 2010.

In a nutshell Guidelines

Questions?

References I



Ahmad, K., Budin, G., Wien, U., Devitt, A., Glucksberg, S., Heyer, G., Leipzig, U., Musacchio, M. T., Pazienza, M. T., Rogers, M., Vogel, C., and Wilks, Y. (2011).

Affective Computing and Sentiment Analysis: Emotion, Metaphor and Terminology, volume 45.

Springer Science+ Business Media.



Barriere, V., Clavel, C., and Essid, S. (2017).

Opinion dynamics modeling for movie review transcripts classification with hidden conditional random fields.

Proc. Interspeech 2017, pages 1457-1461.



Cardon, D. (2013).

La democratie internet promesses et limites. *Polis*, 12(36):545–549.

References II

Clavel, C., Adda, G., Cailliau, F., Garnier-Rizet, M., Cavet, A., Chapuis, G., Courcinous, S., Danesi, C., Daquo, A.-L., Deldossi, M., Guillemin-Lanne, S., Seizou, M., and Suignard, P. (2013). Spontaneous speech and opinion detection: mining call-centre transcripts. Language Resources and Evaluation. Clavel, C. and Callejas, Z. (2016). Sentiment analysis: from opinion mining to human-agent interaction. IEEE Transactions on Affective Computing, 7(1):74–93. Dutrey, C., Clavel, C., Rosset, S., Vasilescu, I., and Adda-Decker, M. (2014). A crf-based approach to automatic disfluency detection in a french call-centre corpus. In Interspeech, page to appear. Langlet, C. and Clavel, C. (2015). Adapting sentiment analysis to face-to-face human-agent interactions: from the detection to the evaluation issues. In Affective Computing and Intelligent Interaction (ACII), 2015 International

Conference on, pages 14–20. IEEE.

References III



References IV



Schuller, B., Ganascia, J.-G., and Devillers, L. (2016). Multimodal sentiment analysis in the wild: Ethical considerations on data collection, annotation, and exploitation.

In Actes du Workshop on Ethics In Corpus Collection, Annotation & Application (ETHI-CA2), LREC, Portoroz, Slovénie.



Strapparava, C. and Valitutti, A. (2004). WordNet Affect: an Affective Extension of WordNet. *LREC*, pages 1083–1086.