

Natural Language Processing for Cognitive Analysis of Emotions

Gustave Cortal¹, Alain Finkel^{1,4}, Patrick Paroubek², and Lina Ye³

¹ Université Paris-Saclay, CNRS, ENS Paris-Saclay, Laboratoire Méthodes Formelles, 91190, Gif-sur-Yvette, France

² Université Paris-Saclay, CNRS, Laboratoire Interdisciplinaire des Sciences du Numérique, 91400 Orsay, France

³ Université Paris-Saclay, CNRS, ENS Paris-Saclay, CentraleSupélec, 91190, Gif-sur-Yvette, France

⁴ Institut Universitaire de France, France

`gustave.cortal@ens-paris-saclay.fr`, `alain.finkel@lsv.fr`, `pap@limsi.fr`, `lina.ye@centralesupelec.fr`

Abstract. Emotion analysis in texts suffers from two major limitations: annotated gold-standard corpora are mostly small and homogeneous, and emotion identification is often simplified as a sentence-level classification problem. To address these issues, we introduce a new annotation scheme for exploring emotions and their causes, along with a new French dataset composed of autobiographical accounts of an emotional scene. The texts were collected by applying the Cognitive Analysis of Emotions developed by A. Finkel to help people improve on their emotion management. The method requires the manual analysis of an emotional event by a coach trained in Cognitive Analysis. We present a rule-based approach to automatically annotate emotions and their semantic roles (e.g. emotion causes) to facilitate the identification of relevant aspects by the coach. We investigate future directions for emotion analysis using graph structures.

Keywords: Sentiment Analysis · Aspect-Based Emotion Analysis · Natural Language Processing · Cognitive Analysis of Emotions · Rule-Based system

1 Introduction

1.1 Cognitive Analysis of Emotions

Similar to many psychological theories (e.g. Freud’s psychoanalysis, Perls’ Gestalt therapy, Greenberg’s Emotion-focused therapy, Shapiro’s Eye Movement Desensitization and Reprocessing and most psychological theories of emotions including Appraisal Theory), the Cognitive Analysis of Emotions (CAE) (Finkel, 2022) considers that the mind, in a given scene, processes emotions and associated cognitions according to a cycle. For the most part, this process is not conscious and begins with the identification of a situation and its issues. Then, it is followed by a reflection concerning the benefits and disadvantages of possible choices of actions. A decision is made, and the chosen action is executed. Finally, the cycle ends with a return to a ready state that is able to process the next scene.

For instance, I am waiting for my turn to take a ticket at the cash desk of the cinema when someone passes me. I feel angry because I think neither I nor the social rules have been respected. I evaluate my possible actions and their consequences: protest verbally, physically push the person away, do nothing or run away. As my fear of a conflict overtakes my anger, I decide to keep quiet and do nothing.

The conflict I avoided in the outside world may be internalized in my mind. I may be angry at the part of myself that didn’t defend my rights, or I may be sad to be separated from my vision of a fair world. In this example, the emotion processing cycle did not go as well as possible. I remain mentally preoccupied after the scene. I have regrets and doubts. I mentally replay the scene differently.

The CAE is part of discrete emotion theory as it studies how the four primary emotions (joy, sadness, anger and fear) appear in autobiographical accounts describing brief scenes (lasting a few tens of seconds) with emotions experienced by the author. One of CAE assumptions is that an emotion coming to our consciousness is a message to solve a problem (in the sense of problem-solving) associated with this emotion.

The universal problems, signaled by the four primary emotions, are formalized through the notion of territory. The previous scene stages an attack on the following two territories: my free time (constrained by the cinema queue) and my comforting vision of an organized and predictable world with laws accepted by almost everyone. Anger and fear are signals that at least one of our territories is under attack. It is up to us to defend (anger) or flee (fear) from it. Joy and sadness are signals that a change in our connection to a territory has occurred. For

example, I may be joyful if I get a distinction in my master’s degree because my important object *positive self-image* will be reinforced. If I decide to work abroad, I may be sad because I will be physically separated from my important object *family*. Territories and objects are related to human needs that have to be satisfied. For example, according to Maslow’s hierarchy of needs (Maslow, 1943), human beings have physiological, safety, love and belonging, esteem, and self-actualization needs. In this paper, we propose to understand emotions and their causes by automatically identifying the relevant territories and objects involved in an emotional scene.

1.2 Autobiographical accounts of an emotional scene

In a CAE session, people who want to better manage their emotions write down an autobiographical narrative of a past emotional scene they experienced, in a given place and time, with identified characters. The coach imposes instructions for writing the scenes. These instructions represent textual metadata that will make easier the construction of an emotion analysis dataset. The author writes the account in four major parts:

- *Facts* describe the behaviors that are observable by everyone in the scene. This part also includes thoughts and physical feelings experienced by the author, because internal events are not observable but presumed “true”, as not refutable.
- *Emotions* identify the emotions experienced by the author. Observable emotions of other participants can be considered as *Facts*.
- *Reasons* identify the emotion causes according to the territory theory of the CAE. Relevant territories and objects are identified.
- *Actions* analyze the past actions, mentally replay the scene in the present and test possible actions for the future. The goal is to find the best actions adapted to the situation.

The CAE coach helps the author to identify, from the guided analysis of her or his account, the relevant territories and objects that are in play in an emotional scene. The coach’s analysis aims to understand emotion causes and suggests corrective actions to better handle situations. In the next section, we describe the model we developed to automatically identify semantic roles (e.g. EXPERIENCER, TERRITORY, OBJECT, etc.) in a text. The proposed solution aims to automate an important step of CAE analysis, namely the identification of emotions and their causes.

2 Emotion modelling based on Cognitive Analysis of Emotions

2.1 Sentiment and Emotion analysis

Since its introduction by Pang et al. (2002) two decades ago, sentiment analysis (a.k.a. opinion mining) has become an influential field of research with widespread applications in industry. However, the majority of research on sentiment analysis considers it as merely text or content categorization task (Poria et al., 2020), i.e. classifying into two or three categories of sentiments: positive, negative, or neutral. In other words, sentiment analysis rarely takes into account the psychological aspect to really understand the sentiments and their causes. On the contrary, emotion detection aims at identifying distinct human emotion types expressed in texts, audio or videos (Varni et al., 2020). Besides studying the so-called primary 4-scale emotions, emotion detection also handles higher scale and even circumflex models, depending on both psychology theories and emotion models (Sailunaz et al., 2018). A review of the existing annotated text datasets for emotion analysis has been done by Bostan and Klinger (2018).

2.2 French dataset for Aspect-Based Emotion Analysis

Some corpora with emotion annotation exist for French, e.g. the DEFT 2018 emotion, sentiment and opinion identification shared task dataset (Paroubek et al., 2018) or the corpus for recognizing emotions in children’s books (Étienne et al., 2020). However, they cannot be used for CAE for various reasons: the text material or the emotion model is incompatible, there is not enough data for model training, etc.

Our dataset, composed of autobiographical accounts of an emotional scene, will indicate emotions and their semantic roles: CUE (a marker indicating the presence of an emotion, which can be a single word), EXPERIENCER (the author who feels an emotion), TARGET (an entity or a person targeted by an emotion) and CAUSE (an event that triggers an emotion). These roles are employed by Campagnano et al. (2022) to unify several gold but heterogeneous datasets that contain annotations for both emotions and their semantic roles. Hence, instead of considering emotion analysis as a sentence-level classification problem, we focus on the aspect-level. We

propose to deeply understand a given text describing an emotional scene, by automatically identifying who feels an emotion, what drives an entity to express an emotion toward a certain aspect and why. For instance, in this sentence, “Gustave loves carnivorous plants because they are beautiful”, Gustave (EXPERIENCER) exposes his joy (CUE) towards carnivorous plants (TARGET) because they are beautiful (CAUSE).

2.3 Extended scheme for emotion annotation

We propose to extend the annotation scheme with new semantic roles based on CAE to better understand emotion causes. We introduce TERRITORY and OBJECT, corresponding to the notion of territory and object in CAE. We also introduce ATTACK (expressions related to the act of attacking or being attacked, e.g. attack, assault, aggression, etc.) and ATTACKER (an entity that attacks a TERRITORY). Identifying ATTACK and ATTACKER beforehand facilitates the identification of TERRITORY. For instance, in the sentence “My skills are attacked by Marc”, “My skills” are a TERRITORY related to the author’s professional values and competent self-image that is attacked by the ATTACKER “Marc”. These new semantic roles can be seen as a refinement of CAUSE presented above. We also use two complementary roles: MODIFIER for taking into account the intensity of an emotion (e.g. “I’m a **little** sad”) and NEGATION to preserve the original meaning of expressions using negation markers (e.g. “She was **not** angry”).

3 Automatic identification of emotions and their semantic roles

3.1 Rule-based method

We present a rule-based method to automatically identify the semantic roles in autobiographical accounts of an emotional scene. We leverage linguistic features using dependency parsing, co-reference resolution⁵ and part-of-speech tagging with the open source library SpaCy.⁶ Co-reference links are used to connect different expressions referring to the same referent, as it is useful to identify multiple occurrences of the same EXPERIENCER and the same TARGET to better understand the emotional flow in a text.

We use WordNet (Miller, 1994), a lexical database of semantic relations including synonyms, hyponyms, and meronyms, to identify CUES and words related to an ATTACK of a TERRITORY. For the French language, we choose the French WordNet called WOLF (Sagot & Fišer, 2008). Sentiment and emotion lexicons are also used to improve the identification of CUES. SentiWordNet (Baccianella et al., 2010) is built on top of WordNet. In this lexicon, each word sense is assigned with a degree of positivity, negativity, and neutrality. NRC Emotion Lexicon (Mohammad & Turney, 2013) is another popular lexicon, where each word is associated with eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) and two polarities (negative and positive).

As we are working with autobiographical texts, an author often describes oneself with first-person pronouns. It is therefore easy to detect the EXPERIENCER through regular expression filtering. To identify complex semantic roles such as TERRITORY, we manually define several rules using linguistic features. For example, a TERRITORY is found if it is the subject of an ATTACK in passive voice: “**My skills** are attacked by Marc”.

Rule-based methods do not require training data. Explainability of results is one of its major benefits. However, it is sometimes difficult to formulate rules and a task may require a huge amount of rules, leading the method to be highly domain-specific. Coherence and consistency checking time increase drastically with the number of rules. Performance stability on yet unseen data is difficult to assess. At the time of writing, the annotation of the autobiographical accounts has not yet been performed, nor has the evaluation of this first rule-based prototype. This will be done in the near future.

In future work, we will combine our rule-based method with recent deep learning techniques to take the best of both approaches. For example, Ray and Chakrabarti (2022) propose to combine a rule-based method with a deep convolutional neural network to improve the performance of aspect extraction. Li et al. (2021) show that neural taggers can generate new rules based on seed rules, which are manually predefined high quality rules. For our case, the learned rules can potentially explain the predicted semantic roles, and hence discover new ways to identify the emotional content of a text.

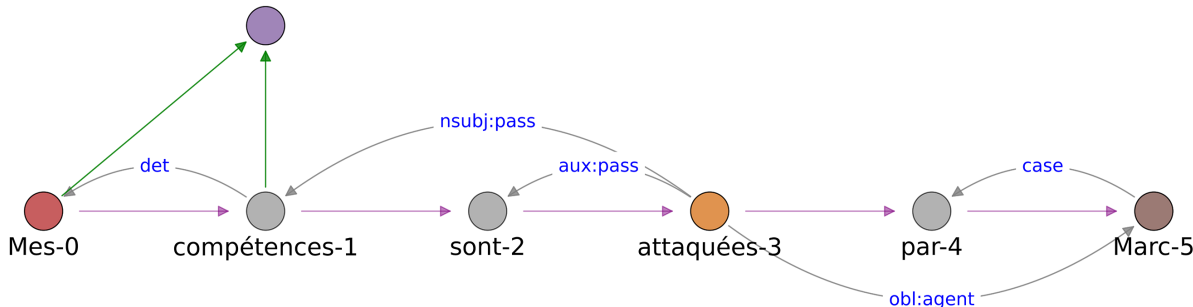


Fig. 1. Visualization of the French sentence: “*Mes compétences sont attaquées par Marc*” (translated “My skills are attacked by Marc”). **Edge colors** indicate different types of relations, e.g. noun chunk membership is in green and sequential relation is in pink (e.g. from *Mes-0* to *compétences-1*). **Node colors** indicate semantic roles, e.g. EXPERIENCER is in red (*Mes-0*), TERRITORY is in purple (*Mes-0 compétences-1*), ATTACKER is in brown (*Marc-5*) and ATTACK is in yellow (*attaquées-3*).

3.2 Graph structure

An emotion is a complex phenomenon that resonates in multiple levels of analysis through different scales. We propose to represent emotion expressions by a graph structure that can be visualized. A sentence or a whole text corresponds to a graph in which nodes are words and edges indicate relations of various kinds between words. We incorporate our rule-based method into the graph structure. Figure 1 illustrates the visualization application built using NetworkX⁷. The application can display different levels of text analysis (e.g. dependency parsing, our emotion analysis, etc.) in a single plane. For instance, co-reference links connect certain semantic roles between them. The relation visualizer can therefore be used to facilitate the manual process of creating rules.

We plan to augment the graph structure with new semantic relations by extracting knowledge paths from ConceptNet (Speer et al., 2017). It is a multilingual semantic network that provides concepts connected with large amounts of semantic relations. For instance, Yan et al. (2021) incorporate commonsense knowledge from ConceptNet to reduce the position bias in Emotion Cause Extraction models. We believe semantic networks can be useful to better capture the dependencies between emotions and their semantic roles, as they leverage commonsense knowledge. Our next goal is to design dedicated graph neural networks such that the specific structural elements of these graphs can be better captured to improve performance. For example, Marcheggiani and Titov (2017) exploit syntactic information using graph convolutional networks to encode sentences, as semantic representations are similar to syntactic ones. The proposed methods can be combined and extended to exploit other information that the graph structure offers.

4 Conclusion

To remedy some limitations in emotion analysis, we propose to deeply understand an emotional scene by performing fine-grained analysis of an emotion and its semantic roles at the aspect-level. We introduce a new annotation scheme, based on Cognitive Analysis of Emotions, along with a new dataset composed of French autobiographical accounts of an emotional scene. As manually analyzing accounts is time-consuming, we provide an automated assistant for the coach, who can therefore focus on aspects that cannot be submitted to automatic processing. Our rule-based method automatically identifies emotions and their semantic roles in a text. In the future, after annotating the autobiographical accounts with our annotation scheme and performing the quantitative evaluation of our rule-based method, we plan to combine it with recent deep learning models (e.g. graph neural networks) through the graph structure we developed to improve performance.

⁵ <https://github.com/pandora-intelligence/crosslingual-coreference>

⁶ <https://spacy.io>

⁷ <https://networkx.org>

References

- Baccianella, S., Esuli, A., & Sebastiani, F. (2010). SentiWordNet 3.0: An enhanced lexical resource for sentiment analysis and opinion mining. *Proceedings of the Seventh International Conference on Language Resources and Evaluation (LREC'10)* (cit. on p. 3).
- Bostan, L.-A.-M., & Klinger, R. (2018). An analysis of annotated corpora for emotion classification in text. *Proceedings of the 27th International Conference on Computational Linguistics*, 2104–2119 (cit. on p. 2).
- Campagnano, C., Conia, S., & Navigli, R. (2022). SRL4E – Semantic Role Labeling for Emotions: A unified evaluation framework. *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 4586–4601 (cit. on p. 2).
- Étienne, A., Battistelli, D., & Lecorvé, G. (2020). L'expression des émotions dans les textes pour enfants : Constitution d'un corpus annoté (expressing emotions in texts for children: Constitution of an annotated corpus). *Actes de la 6e conférence conjointe Journées d'Études sur la Parole (JEP, 33e édition), Traitement Automatique des Langues Naturelles (TALN, 27e édition), Rencontre des Étudiants Chercheurs en Informatique pour le Traitement Automatique des Langues (RÉCITAL, 22e édition). Volume 2 : Traitement Automatique des Langues Naturelles*, 205–212 (cit. on p. 2).
- Finkel, A. (2022). *Manuel d'analyse cognitive des émotions: Théorie et applications*. Dunod. (Cit. on p. 1).
- Li, J., Ding, H., Shang, J., McAuley, J., & Feng, Z. (2021). Weakly supervised named entity tagging with learnable logical rules. *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, 4568–4581 (cit. on p. 3).
- Marcheggiani, D., & Titov, I. (2017). Encoding sentences with graph convolutional networks for semantic role labeling. *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, 1506–1515 (cit. on p. 4).
- Maslow, A. H. (1943). A theory of human motivation. *Psychological Review*, 50, 370–396 (cit. on p. 2).
- Miller, G. A. (1994). WordNet: A lexical database for English. *Human Language Technology: Proceedings of a Workshop held at Plainsboro, New Jersey, March 8-11, 1994* (cit. on p. 3).
- Mohammad, S. M., & Turney, P. D. (2013). Crowdsourcing a word-emotion association lexicon. *Computational Intelligence*, 29(3), 436–465 (cit. on p. 3).
- Pang, B., Lee, L., & Vaithyanathan, S. (2002). Sentiment classification using machine learning techniques. *Proceedings of the 2002 Conference on Empirical Methods in Natural Language Processing, EMNLP 2002, Philadelphia, PA, USA, July 6-7, 2002*, 79–86 (cit. on p. 2).
- Paroubek, P., Grouin, C., Bellot, P., Claveau, V., Eshkol-Taravella, I., Fraisse, A., Jackiewicz, A., Karoui, J., Monceaux, L., & Torres-Moreno, J.-M. (2018). DEFT2018 : Recherche d'information et analyse de sentiments dans des tweets concernant les transports en Île de France (DEFT2018 : Information retrieval and sentiment analysis in tweets about public transportation in Île de France region). *Actes de la Conférence TALN. Volume 2 - Démonstrations, articles des Rencontres Jeunes Chercheurs, ateliers DeFT*, 219–230 (cit. on p. 2).
- Poria, S., Hazarika, D., Majumder, N., & Mihalcea, R. (2020). Beneath the tip of the iceberg: Current challenges and new directions in sentiment analysis research. *IEEE Transactions on Affective Computing*, 1–1 (cit. on p. 2).
- Ray, P., & Chakrabarti, A. (2022). A mixed approach of deep learning method and rule-based method to improve aspect level sentiment analysis. *Applied Computing and Informatics*, 18(1), 163–178 (cit. on p. 3).
- Sagot, B., & Fišer, D. (2008). Building a free French wordnet from multilingual resources. *OntoLex* (cit. on p. 3).
- Sailunaz, K., Dhaliwal, M., Rokne, J. G., & Alhaji, R. (2018). Emotion detection from text and speech: A survey. *Soc. Netw. Anal. Min.*, 8(1), 28:1–28:26 (cit. on p. 2).
- Speer, R., Chin, J., & Havasi, C. (2017). Conceptnet 5.5: An open multilingual graph of general knowledge. *Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence*, 4444–4451 (cit. on p. 4).
- Varni, G., Hupont, I., Clavel, C., & Chetouani, M. (2020). Computational study of primitive emotional contagion in dyadic interactions. *IEEE Transactions on Affective Computing*, 11(2), 258–271 (cit. on p. 2).
- Yan, H., Gui, L., Pergola, G., & He, Y. (2021). Position bias mitigation: A knowledge-aware graph model for emotion cause extraction. *arXiv preprint arXiv: Arxiv-2106.03518* (cit. on p. 4).