



**HAL**  
open science

# A formal representation of appraisal categories for social data analysis

Valentina Dragos, Delphine Battistelli, Emmanuelle Kellodjoue

► **To cite this version:**

Valentina Dragos, Delphine Battistelli, Emmanuelle Kellodjoue. A formal representation of appraisal categories for social data analysis. *Procedia Computer Science*, 2020, Knowledge-Based and Intelligent Information & Engineering Systems: Proceedings of the 24th International Conference KES2020, 176, pp.928 - 937. 10.1016/j.procs.2020.09.088 . hal-03184135

**HAL Id: hal-03184135**

**<https://hal.science/hal-03184135>**

Submitted on 29 Mar 2021

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



24th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems

# A formal representation of appraisal categories for social data analysis

Valentina Dragos<sup>b\*</sup>, Delphine Battistelli<sup>a</sup>, Emmanuelle Kellodjoue<sup>a,b</sup>

<sup>a</sup> *MODYCO, CNRS-Paris Nanterre University, 92001 Nanterre, France*

<sup>b</sup> *ONERA - The French Aerospace Lab, 91 123 Palaiseau, France*

---

## Abstract

Human behavior is impacted by subjective states although currently the cyberspace becomes a replacement for real-life spaces and interactions. As social media platforms change people's lives and impacts the way they communicate and group themselves into virtual networks of like-minded individuals, the analysis of online content offers valuable insights of processes taking place on the Internet. Social data mining revolves around subjective content analysis, which deals with the computational processing of texts conveying people's evaluations, beliefs, attitudes and emotions. Opinion mining and sentiment analysis are the main paradigm of social media exploration and both concepts are often interchangeable. This paper investigates the use of appraisal categories to explore data gleaned for social media and describes the construction of a formal model describing the way language is used in the cyberspace to evaluate, express mood and affective states, construct personal standpoints and manage interpersonal interactions. The ontology offers a mean to investigate subjective content going beyond the traditional notions of opinion and sentiment. Pitfalls of building a formal model for appraisal categories are examined and limitations of using the model for social data exploration are discussed.

© 2020 The Authors. Published by Elsevier B.V.

This is an open access article under the CC BY-NC-ND license (<https://creativecommons.org/licenses/by-nc-nd/4.0>)

Peer-review under responsibility of the scientific committee of the KES International.

*Keywords:* ontology; appraisal theory, social data; opinion detection; sentiment analysis

---

---

\* Corresponding author. Tel.: +0-000-000-0000 ; fax: +0-000-000-0000 .

*E-mail address:* [valentina.dragos@onera.fr](mailto:valentina.dragos@onera.fr)

## 1. Introduction

Analysis of social data comes with challenges for traditional data mining approaches that are often too slow and expensive, rely on sample sizes, and come with biases leading to errors. Social media data are vast, noisy, unstructured, inherently dynamic and heterogeneous in nature. Moreover, they convey author's personal points of view and processing solutions fall under the umbrella of sentiment analysis and opinion mining [5], a natural language processing task dealing with automatic processing of people's evaluations, attitudes, and emotions as expressed in written language. While sometimes those concepts are interchangeable, it is generally accepted that opinion mining considers not only the sentiment conveyed by written stances, but also the topics driving that sentiment.

From a content analysis standpoint, social media users are rather vocal, often turning to online platforms to express their tastes. Exploring online media comes with unprecedented opportunities for a broad category of applications, among which intelligence analysis and homeland security can explore the huge amount of data for insights allowing them to understand and to some degree predict new phenomena. Given the diversity of topics covered, the variety of user profiles, the huge volume of data submitted on a daily basis and the difficulties of social data processing, an effective solution for social data exploration should be model-driven.

This paper tackles the construction of the appraisal ontology, a formal representation grounded on cognitive foundations that offers a mean to detect subjective stances and harness affective states within content released by users on the Internet. The model is built upon the foundations of the appraisal theory developed by White and Martin [17] and provides categories making the distinction between affect, appreciation or judgement. The appraisal frame considers the meanings by which text convey positive and negative attitudes, and takes into account the way such utterances are strengthened or weakened by author's thanks to linguistic clues of intensity. Adopting appraisal categories allows going beyond the limitations of opinion and sentiment, and presents author's feelings, tastes and opinions with greater or lesser intensity.

The remainder of the paper is organized as follows: next section discusses approaches developed for social data analysis, with emphasis on ontology-driven solutions. Section 3 introduces main notions of the appraisal theory and section 4 presents the construction of an ontology for their formal representation. Construction pitfalls and limitations of the model are discussed in section V. Conclusion and perspectives for future work end this paper.

## 2. Related approaches

Methods developed for social data exploration analyse the implicit, explicit and discursive patterns hidden in volumes of online data [28], [22] and can be roughly divided into machine-learning methods and lexicon-based methods [25]. This section presents a selection of methods of the former class. Several approaches investigate social data exploration by using lexicons or ontologies developed to detect features of subjectivity within textual content. Thus, SenticNet 2.0 [9] offers a collection of around 100,000 natural language concepts, described in terms of four affective dimensions (Pleasantness, Attention, Sensitivity, and Aptitude) and also having a polarity assignment, as a floating number between -1 and +1, where -1 is negative polarity and +1 is positive polarity.

A Sentiment Treebank is used in [21] to provide fine grained sentiment labels for around 215 000 phrases and to allow sentiment compositionality. The Treebank is used to train a recursive neural tensor network, and the authors show that the model outperforms previous opinion detection methods on several metrics, while being able to accurately capture the effect of contrastive conjunctions and negations. Domain adaptation is still a challenge for lexicon-based approaches, and Bollegala et al. describe in [6] a solution using a distributional thesaurus to expand feature vectors during training and testing phases of a binary classifier. The lexicon provides a set of labelled data for the source domain and unlabelled data for both source and target domains, and sensitivity attributes are added for each word by measuring their distributional similarity.

Taking a step forward, several approaches analyse not only the word, but also the context [15] and workarounds, in an effort to harness sentiment expression forms unique to data to be processed. Among them, SentiStrength [27] is an algorithm developed by to detect the intensity of sentiments by using a list of 2,489 positive and negative sentiment stems and strengths, and combination rules to estimate the overall sentiment and strength at phrase level

by combining their values. They also take into account linguistic boosters and downtoners, and the approach is suitable to analyse short text gleaned on social media, which often lacks standard grammar and spelling. In the same line, the solution described in [26] learns word embeddings to classify Twitter corpora. The approach models the syntactic context of word and also encodes sentiment information in the continuous representation of words. The overall solution shows good accuracy but requires a large scale training corpora.

However, such relatively robust techniques, grounded on linguistic bases, come with a main drawback, as they are inflexible regarding the ambiguity of terms conveying sentiments, orientations and polarity. Moreover, the context in which a term occurs slightly modifies its meaning and several studies [13] have shown that adding contextual [29], [30] or crossdomain [10] information can improve the estimation of ambiguous polarity [16]. The use of ontologies for social data sensing was investigated by several research efforts. Among them, [14] uses a formal model as a mean to derive knowledge from collections of tweets, while [2] implements a text mining approach that is driven by an ontology to explore social networks. Those solutions have various applications, ranging from detecting depression signals for teenagers [12] to crisis management using stream off online data [31].

Although most applications use ontologies to capture domain knowledge, several models have been developed to represent affective states and their influences according to psychological theories [1]. This paper describes the construction of an ontology modeling appraisal categories for social data exploration. This is an emergent topic and currently there are few approaches currently using the appraisal theory for social data analysis, addressing namely the construction of a semantic resource [23] to detect sentiments and the use of appraisal categories to analyse microblogs [3] and news [15]. The development of a new ontology was needed as existing models prove to be inappropriate for the purpose of social data exploration.

### 3. Overview of the appraisal theory

The Appraisal Theory is a cognitive frame claiming that people's emotions are elicited by their personal and continuous interpretations, evaluations or appraisals of objects, events and situations. The most important aspect of the appraisal theory is that it provides a way to express how humans interpret some particular event as positive or negative along with their position, support and engagement with respect to their own interpretation and report: confidence, support, agreement, disagreement, deny, rejection. From a linguistic standpoint, the appraisal theory describes how authors use linguistic expressions to communicate their emotional states and engagement. The appraisal framework goes beyond limitations of traditional concepts of sentiment and opinions and considers the appraisal expression, which is a linguistic unit by which a personal appreciation is conveyed, whether it is an opinion, sentiment or supportive statement. The appraisal theory structures appraisal expressions under three main basic systems describing attitudes, engagement and graduation, as shown in fig. 1.

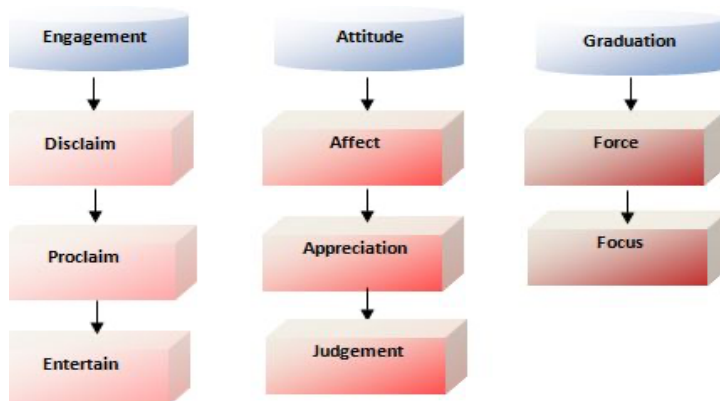


Fig. 1. Systems of the appraisal theory

The attitude system is related to linguistic expressions conveying the current of authors at the time they write the text and. This system covers three main subcategories: affect, appreciation and judgement, discussed hereafter.

- Affect is related to linguistic expressions of author's feelings such as happiness, joy, sadness, grief, etc., as shown in sentences hereafter:

*S1: This movie **bores** me.*

*S2: Helping others makes me **happy**.*

- Judgment highlights linguistic expressions conveying characterization of persons and behaviors by the author. Generally it conveys opinions and personal tastes about objects, such as nice, ugly, beautiful, shy but also about interactions and behaviors in the social context: heroic, brave, open-minded, feeble-minded, see sentences below:

*S4: Paul is **rude**, but **honest**.*

*S5: They are a **kind** nation.*

- Appreciation is related to assessment and evaluations of entities, objects, events and scenes, as shown in examples:

*S5: The painting is **beautiful**.*

*S5: My phone is **useless**.*

The engagement system gathers linguistic expression specifying the author's position with respect to his own statements. When reporting, writers often embed clues as to how strongly they support the content being conveyed and may indicate confidence, doubt, skepticism, conviction, etc., about the information reported. The engagement system is closely related to the notions of trust, confidence, probability or possibility. Categories under this system are depicted in fig. 2 and encompass aspects related to denial (S6), concession (S7), confirmation (S8), endorsement (S9), acknowledgement (S10) and distance (S11).

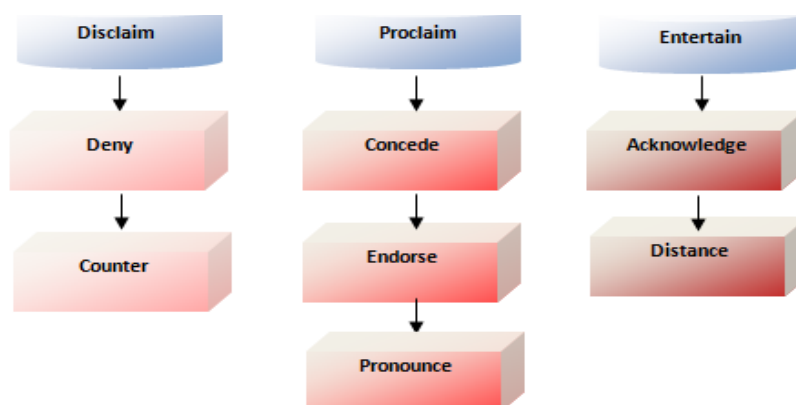


Fig. 2. The engagement system

*S 6: You **don't need** to access the file.*

*S7: **Although** it was raining we went out.*

*S8: **Of course** Brexit was unexpected*

*S9: The reports **show** he was involved in the accident.*

*S10: **According to Times**, he is leading the election*

*S11: **Many are claiming** that he will not win.*

The graduation is the last system of the appraisal theory and it is introduced in order to provide means to measure or at least estimate the orientation and various degrees of intensity associated to affect, appreciations, judgment and engagement. The system is composed of Force and Focus, and is conveyed by linguistic modifiers such as intensifiers (very, enough, etc.) and downtoners (few, low, etc.).

In order to implement automatic procedures to identify appraisal expressions, a formal ontology [11] was built to represent main concepts and their linguistic instances and make explicit relationships. The construction of this ontology is described in the next chapter.

#### 4. A formal model of appraisal categories

Ontologies are formal representations of domain knowledge. The appraisal ontology was built in order to have a general description of appraisal categories and to provide a formal model of concepts and the set of relations. There are currently several ontologies developed to support opinion mining and sentiment analysis developed to investigate features of subjectivity within textual content. The development of a new ontology was needed as existing models prove to be inappropriate for the purpose of this work as they are tailored for different applicative scenarios. The main drawback of existing resources is the lack of concepts specific to Engagement system. The ontology was created from scratch, as there are no appraisal experts and the construction process was guided when needed by two existing general resources: WordNet [18] and SenticNet [7]. The main step of ontology construction is conceptualization, which identifies main concepts and relations. The model created with Protégé [19] and formalized using OWL DL language [4].

##### 4.1. Modeling concepts

Starting with categories introduced by the appraisal theory, and adding additional concepts to characterise appraisal expressions, six main concepts were identified (fig. 3) to model: attitude, engagement, graduation, orientation, polarity and modifiers.

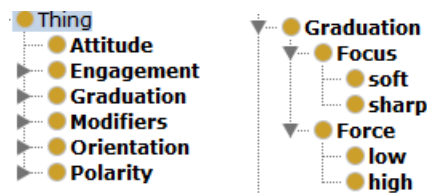


Fig. 3. Main concepts of the ontology Fig. 4 Graduation concepts

Among appraisal categories, attitude and engagement are modeled as introduced by the appraisal theory, but with finer description of their sub-categories, as shown in tab. 1 and II.

TABLE I. SUBCLASSES OF ATTITUDE SYSTEM

Classes	Attitude System	
	Sub-classes	Instances
Affect	-	Happy, joyful, miserable
Appreciation	Composition	Detailed, consistent
	Impact	Amazing, monotonous
	Valuation	Innovative, profound
Judgement	Social esteem	Brave, disloyal , clever
	Social sanction	Virtuous, corrupt , honest

TABLE II. SUBCLASSES OF ENGAGEMENT SYSTEM

Classes	Engagement System	
	Sub-classes	Instances
Disclaim	Deny	No, didn't, never
	Counter	Yet, although, but
Proclaim	Concur	Naturally, obviously
	Pronounce	Indeed
	Endorse	Demonstrates, shows, proves
Entertain	-	Perhaps, probable, apparently
Attribute	Acknowledge	It's said that, many argues,
	Distance	He claimed to

Graduation concept was enriched by adding several subclasses to describe Focus as sharp or soft and Force as high or low, as shown in fig. 4. For all those categories linguistic examples were also added at instance level.

Modifiers shown in fig. 5 is a concept intended to capture the ability of linguistic markers to increase (fig. 6), decrease or reverse the intensity of appraisal expressions.

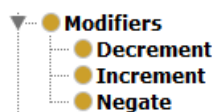


Fig. 5 Modifier concept

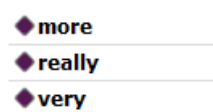


Fig 6 Incremental modifiers

Orientation is a concept used to capture positive and negative emotional states conveyed by appraisal expressions and polarity is used to make explicit the presence of negation markers (in this case polarity is marked otherwise it is considered as unmarked).

#### 4.2. Modeling relations

Besides is-a relations used to create the hierarchical structure of concepts, 6 relations were added to connect concepts on the ontology, see tab. III.

TABLE III. ONTOLOGY RELATIONS

Name	Relation	
	Source	Target
hasGraduation	Engagement	Graduation
hasPolarity	Engagement	Polarity
hasOrientation	Engagement	Orientation
Increase	Modifier	Force
Decrease	Modifier	Force

#### 4.3. Description of the ontology

The model is composed of 46 concepts with a 6 levels hierarchy; the model also has 4 Object Properties and 2 DataType Propertie, 50 nodes, 75 edges and 268 instances of concepts.

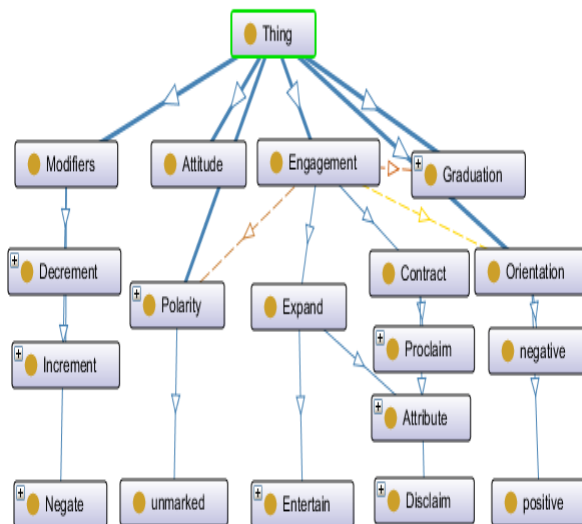


Fig. 7 Ontology of appraisal categories

Once concepts and relationships were modeled by ontology, linguistic instances were added by using WordNet, a lexical resource for English clustering similar terms into synsets and highlighting synonymy and antonymy relations. Association of concept to orientation and force was guided by SenticNet, a resource providing polarity associated with 100,000 natural language concepts that are also described in terms of four affective dimensions (Pleasantness, Attention, Sensitivity, and Aptitude).

4.4. Yet another ontology for opinion mining

There are currently several ontologies developed to support opinion mining and sentiment analysis developed to investigate features of subjectivity within textual content. The development of a new ontology was needed as existing models prove to be inappropriate for the purpose of this work as they are tailored for different applicative scenarios. The main drawback of existing resources is the lack of concepts specific to Engagement system. Moreover, those resources captures different meanings, namely for aspects related to engagement, confidence and belief, as shown in fig. 8.

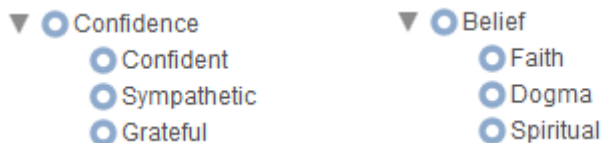


Fig. 8 Concepts Confidence and Belief modelled by SenticNet

The main contribution of the appraisal ontology is to provide a formal model according to categories introduced by the appraisal theory, to refine their structure for a multi-layered description and to gather linguistic instances for concepts. While orientation and polarity are assigned at instance level thanks to data properties hasOrientation and hasForce, the structure of ontology allows the construction of both coarse and fine-grained description of textual content conveying instances of concepts.



## 5. Pitfalls and limitations of ontology construction

One of the benefits of building formal representations is their potential to be shared and reused. However, practical pitfalls affect the construction of an ontological representation and the model has several limitations, discussed hereafter.

### 5.1. Modeling nonfunctional domains

The ontology was constructed to capture features of subjectivity according to principles of the appraisal theory. However, the model is not build to describe a functional domain, such as aeronautics or space, having well defined concepts and interactions. Thus, the ontology has a limited number of horizontal relations, describing interactions of concepts and strives to represent the terminological components of concepts. The terminological dimension is emphasized by adding instances of concepts, and also by highlighting how a broader or narrower meaning can be created by linguistic adjustments. Moreover, elements of the model are drawn from the realm of thesauri and semantic lexicons, as there are no sources to describe subjectivity and there are no domain experts to guide the modeling process.

### 5.2. Impact of linguistic phenomena

The main impact from linguistic standpoint is due to the fact that the meaning of words usually depends on the context in which they occur. More specifically, the polarity of words can change according to the context in which they are being used. Although polarity of “good”, “bad” or “excellent” remains the same in all context, “small” is a example of polarity ambiguous word, having a positive orientation in sentences like “small desynchronization”, rather negative when used as “small capacity” and rather neutral in “small world”. As polarity is modeled as a concept of the ontology having three exclusive values (positive, negative and neutral), overcoming limitations dues to ambiguous polarity requires the implementation external procedures, able to detect the occurrence context of words and infer their polarity accordingly.

### 5.3. Completeness and relevance of the model

The final set of limitations concerns the development of a computational model of the appraisal theory. First, there are limitations intrinsic to the cognitive framework, according to which events can trigger more than one affective response simultaneously with various intensity levels although the theory does not provide a clear strategy to select an affective state during the appraisal process [24]. This limitations has direct impacts on the modeling process, as there is no guidance as to how to add relations in the ontology, how to and instances of concepts and how to craft a set of rules for inferences. To overcome this limitation, [20] adopts the development of a domain-independent core-model, to be further augments with ethical procedures for practical applications. The solution described in this paper is in line with this approach, as the model is constructed regardless of its intended application. In addition to limitations cited above, the use of ontology for social data analysis might be able to also highlight task-related drawbacks, such as modeling only concepts and relations in English, although some social media messages are a mix of words written in several languages.

## 6. Conclusion

This paper discusses the construction of a formal representation of appraisal categories, capturing the linguistic dimension of affective states and processes as stated by the appraisal theory. Using the ontology for social data exploration will allow to implement procedures going beyond the generally accepted definitions of sentiment and opinions, and focusing rather on appraisal expressions, as introduced by the appraisal framework to describe the way humans express various degrees of attitudes, appreciations, and engagement. The ontology models main systems of the cognitive framework, gathers terms associated to each system and highlights their various degrees of positive or negative orientations. The model was created from scratch, exploiting several linguistics resources and thesauri, and is completely independent of its intended application domain.

Future work concerns the exploitation of the ontology for social data exploration [8], but also in different contexts such as controversy analysis or contradiction detection [9]. Those various applications will offer a mean for the empirical validation of the model.

## Acknowledgements

This document has been produced in the context of the PRACTICIES project. The research leading to these results has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 740072.

## References

- [1] Abaalkhail, R., Guthier, B., Alharthi, R., & El Saddik, A. (2017). Survey on ontologies for affective states and their influences. *Semantic web*, (Preprint), 1-18.
- [2] K..M., Asam, K. M., & Chatwin, C. R. (2012, June). Ontology-based text-mining model for social network analysis. In *Management of Innovation and Technology (ICMIT), 2012 IEEE International Conference on* (pp. 226-231). IEEE
- [3] A. Balahur, J.M.,Hermida, and A., Montoyo., Building and exploiting emotinet, a knowledge base for emotion detection based on the appraisal theory model. *IEEE Transactions on Affective Computing*, 3(1), 88-101., 2012.
- [4] S., Bechhofer, OWL: Web ontology language. In *Encyclopedia of Database Systems* (pp. 2008-2009). Springer US, 2009.
- [5] B., Bing. Sentiment analysis and opinion mining. *Synthesis lectures on human language technologies*, , vol. 5, no 1, p. 1-167, 2012
- [6] D.,Bollegala, D. Weir, and J.,Carroll, Cross-domain sentiment classification using a sentiment sensitive thesaurus. *IEEE transactions on knowledge and data engineering*, 25(8), 1719-1731, 2013.
- [7] E., Cambria, C., Havasi, and A. Hussain, SenticNet 2: A Semantic and Affective Resource for Opinion Mining and Sentiment Analysis. In *FLAIRS, 2012*.
- [8] V., Dragos, V., D., Battistelli, & E., Kelodjoue,. (2018, July). Beyond Sentiments and Opinions: Exploring Social Media with Appraisal Categories. In *2018 21st International Conference on Information Fusion (FUSION)* (pp. 1851-1858). IEEE.
- [9] V. Dragos, (2017). Detection of contradictions by relation matching and uncertainty assessment. *Procedia Computer Science*, 112, 71-80.
- [10] S. Gindl, A. Weichselbraun, and A. Scharl, Crossdomain contextualisation of sentiment lexicons. In *Proceedings of 19th European Conference on Artificial Intelligence (ECAI-2010)*, pages 771–776, 2010.
- [11] T. Gruber, A translation approach for portable ontology specification, *Knowledge Acquisition* 5(2), 199-220, 1993.
- [12] H., Jung, H.A., Park, & T.M.,Song (2017). Ontology-based approach to social data sentiment analysis: detection of adolescent depression signals. *Journal of medical internet research*, 19(7).
- [13] I, Kaur, T. K., Bhatia, & A., Verma, (2017). Agile Model Based Sentiment Analysis from Social Media. *International Journal of Computer Science and Information Security*, 15(1), 433.
- [14] E. Kontopoulos, C., Berberidis., T., Dergiades, & N., Bassiliades (2013). Ontology-based sentiment analysis of twitter posts. *Expert systems with applications*, 40(10), 4065-4074.
- [15] P., Korenek, and M. Šimko, Sentiment analysis on microblog utilizing appraisal theory. *World Wide Web*, 17(4), 847-867, 2014.
- [16] A. C. E., Lima, L. N., de Castro, J. M. & Corchado, (2015). A polarity analysis framework for Twitter messages. *Applied Mathematics and Computation*, 270, 756-767.
- [17] J.R. Martin, and P. R. White, *The language of evaluation*(Vol. 2). Basingstoke: Palgrave Macmillan, 2003
- [18] G. A. Miller, WordNet: a lexical database for English, *Communications of the ACM*, 38(11), 39-41, 1995.
- [19] N. F., Noy, M., Crubézy, R. W., Ferguson, H., Knublauch, S.W., Tu, J., Vendetti, and M. A., Musen, Protege-2000: an open-source ontology-development and knowledge-acquisition environment. In *AMIA Annu Symp Proc* (Vol. 953, p. 953), 2003.
- [20] S., Ojha, J., Vitale, & M.A., Williams (2017, July). A domain-independent approach of cognitive appraisal augmented by higher cognitive layer of ethical reasoning. In *Annual Meeting of the Cognitive Science Society*
- [21] S., Ojha., & M.A. Williams, (2017, May). Emotional appraisal: A computational perspective. In *Fifth Annual Conference on Advances in Cognitive Systems*.
- [22] A.Pak and P. Paroubek. „Twitter as a Corpus for Sentiment Analysis and Opinion Mining". In *Proceedings of the Seventh Conference on International Language Resources and Evaluation*, pp.1320-1326, 2010.
- [23] C., Soo-Guan Khoo, A.,Nourbakhsh, and J. C., Na, Sentiment analysis of online news text: a case study of appraisal theory. *Online Information Review*, 36(6), 858-878, 2012.
- [24] R.,Socher, A., Perelygin, J., Wu, J.,Chuang, C. D., Manning, A., Ng, and C. Potts, Recursive deep models for semantic compositionality over a sentiment treebank. In *Proceedings of the 2013 conference on empirical methods in natural language processing* (pp. 1631-1642), 2013.
- [25] M. Taboada, J., Brooke, M., Tofiloski, K., Voll, and M., Stede. Lexicon-based methods for sentiment analysis. *Computational linguistics*, 37(2), 267-307., 2011.
- [26] D., Tang, F., Wei, N., Yang, M.,Zhou, T., Liu, and B., Qin, B., Learning Sentiment-Specific Word Embedding for Twitter Sentiment Classification. 2014
- [27] M., Thelwall, M., K., Buckley, and G., Paltoglou, Sentiment strength detection for the social web. *Journal of the Association for Information Science and Technology*, 63(1), 163-173, 2012.

- [28] F., Villarroel Ordenes, S., Ludwig, K, De Ruyter, D., Grewal, & M., Wetzels, (2017). Unveiling what is written in the stars: Analyzing explicit, implicit, and discourse patterns of sentiment in social media. *Journal of Consumer Research*, 43(6), 875-894.
- [29] A. Weichselbraun, S. Gindl, and A. Scharl. . A context-dependent supervised learning approach to sentiment detection in large textual databases. *Journal of Information and Data Management*, 1(3):329–342., 2010.
- [30] T. Wilson, J. Wiebe, and P. Hoffmann.. Recognizing contextual polarity: An exploration of features for phrase-level sentiment analysis. *Computational Linguistics*, 35(3):399–433, 2009.
- [31] V., Zavarella, H., Tanev, R., Steinberger & E., Van der Goot (2014). An Ontology-Based Approach to Social Media Mining for Crisis Management. In *SSA-SMILE@ ESWC* (pp. 55-66).