Editorial for the 2^{nd} AAAI-19 Workshop on Affective Content Analysis

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Abstract. The AffCon2019, the second AAAI Workshop on Affective Content Analysis @ AAAI-19 focused on the analysis of emotions, sentiments, and attitudes in textual, visual, and multimodal content for applications in psychology, consumer behavior, language understanding, and computer vision. It included the inaugural CL-Aff Shared Task on modeling happiness. The program comprised keynotes, original research presentations, a poster session, and presentations by the Shared Task winners.

1 Introduction

The second Affective Content Analysis workshop @ AAAI-19 was aimed at engaging the Artificial Intelligence (AI) and Machine Learning (ML) community around the open problems in affective content analysis and understanding, and succeeds the first Affective Content Analysis workshop @ AAAI-18 in New Orleans [10][4]. Affective content analysis refers to the interdisciplinary research space of Computational Linguistics, Psycholinguists, Consumer psychology, and HCI looking at online communication, its intentions and the reactions it evokes. The purpose of the workshop was to bring together cross–disciplinary research and mechanisms for affect analysis, as well as to pool together resources for further research and development. The workshop is supported by a committee of keen and experienced researchers in the field of AI. [5]

The workshop included the first CL-Aff Shared Task on modeling happiness, to stimulate the development of new approaches and methods for affect identification and representation. It focused on the psycholinguistic and semantic characteristics of written accounts of happy moments. Elevent teams participated in a shared task to model and predict the agency and sociality of happy moments in a semi-supervised set up, scalable to larger problems.

[4] https://aaai.org/Library/Workshops/ws18-01.php
[5] For the full Program Committee list, see https://sites.google.com/view/affcon2019/committees?authuser=0

2 Workshop Topics and Format

The workshop presentations incorporated insights from psychologists, psycholinguists, and computer science researchers to develop new approaches that address open problems such as deep learning for affect analysis, leveraging traditional affective computing (multi-modal datasets), privacy concerns in affect analysis, and inter-relationships between various affect dimensions. These fall under the broad topics of interest of the workshop:

- Affect and Cognitive Content Measurement in Text
- Computational models for Consumer Behavior theories
- Psycho–demographic Profiling
- Affect–based Text Generation
- Spoken and Formal Language Comparison
- Stylometrics, Typographics, and Psycho-linguistics
- Affective needs and Consumer Behavior
- Measurement and Evaluation of Affective Content
- Affective Lexica for Online Marketing Communication
- Affective human-agent, -computer, and-robot interaction
- Multi-modal emotion recognition and sentiment analysis

3 Overview of the papers

The workshop featured four keynote talks, three paper sessions, and a poster session. 33 papers were submitted to the workshop, 11 of which were Systems for the CL-Aff shared task. Finally, 3 papers were accepted as full papers and 4 were accepted as posters, and these will be included in the proceedings. In addition, the winners from the CL-Aff task presented talks and posters at the workshop. One pre-published paper was also invited for the poster session.

The following sections briefly describe the keynote and sessions.

3.1 Keynotes

The workshop had a range of keynote speakers. Dr. Ellen Riloff [6] shared her work in the space of identifying affective events and the reasons for their polarity. She introduced affective events as experiences that positively or negatively impact on our lives and then discussed recent work on identifying affective events and categorizing them based on the underlying reasons for their affective polarity. The discussion included a description of a weakly supervised learning method to induce a large set of affective events from a text corpus, learning models to classify affective events based on Human Need Categories, and concluded with a discussion on directions of future work on this topic.

Dr. Alon Halevy [7] talked about affective search. His talk was centered around the space of positive psychology. He described two works in this space that

[6] http://www.cs.utah.edu/ riloff/

[7] https://homes.cs.washington.edu/ alon/

develop new AI techniques for enabling technology that help individuals increase their well-being. The first work was based on deriving insights from user's notes and second one explained affective search in online ecommerce applications. His talk gave an insight towards potential applications of affective analysis in real world applications.

Dr. Lyle Ungar [8] talked about the use of user generated content for affect analysis. In this talk a study for computational modeling of empathy is presented. Social media language, combined with questionnaires is used to reveals that empathy has both 'good' (compassionate) and 'bad' (depleting) components, with 'bad' empathy associated with stress, reduced perceived control, and reduced well-being, all of which can be measured through peoples' social media language. He also discussed the utility of a novel annotation methodology in which subjects react to news stories both in free text and in multi-item questionnaire responses.

Last but not the least, Dr. Rada Mihalcea [9] discussed her work on grounded emotions. In this talk, she discussed several types of external factors and showed their impact and correlation with a users emotional state. Finally, she presented a study that proved that combining all extrinsic features leads to a decent predictive model for the emotional state of a user.

3.2 Papers:

The workshop included 3 full paper presentations and 4 posters.

Kowalczyk et. al [29] presented their work on privacy aware scalable polarity detection in Twitter. They first argue that strict alignment of data acquisition, storage and analysis algorithms is necessary to avoid the common trade-offs between scalability, accuracy and privacy compliance. In their paper, they propose a new framework for acquisition of large-scale datasets, high accuracy supervisory signal and multilanguage sentiment prediction while respecting every privacy request applicable. Finally, a novel gradient boosting framework is proposed to achieve stateof- the-art results in virality ranking, already before including tweet's visual or propagation features. An empirical analysis across 18 languages shows the generality of this work.

Joshi et al [26] design a joint loss function to optimize the performance of Long Short Term Memory networks for predicting the valence from audio features in a dataset of Academy Award Movies. Drawing from psychology, they model arousal-valence interdependence in two ways and demonstrate a remarkable improvement in predicting valence over an independent valence model.

Qiu et al [57] work on multimodal emotion recognition with a new model they call "Adversarial and Cooperative Correlated Domain Adaptation". They demonstrate higher emotion classification accuracy on datasets comprising physiological signals and eye movements, by following a deep canonical correlation analysis approach that leverages the complementarity of multimodal signals.

[8] http://www.cis.upenn.edu/ ungar/

[9] https://web.eecs.umich.edu/ mihalcea/

Their domain adaptation approach outperforms the state of the art approaches on the SEED IV dataset for four emotion tasks, as well as on the DEAP dataset for two dichotomies.

3.3 Posters

The paper by Tiam-Lee and Sumi [76] provides an analysis of the emotional experiences of students as they learn to program. They focus particularly on the transitions across different emotions and relate facial expressions, body posture and click logs in relation to emotional states. This preliminary study reported subjective differences both in self-reported data and in the facial expressions automatically captured by the system, which highlights the need to design systems and experiments that are conscious of social and cultural norms.

The paper by Luo, Xu, and Chen [35] proposes an model to mine sentiment information in audio. It uses multiple traditional acoustic features and spectrum graphs, and is language insensitive as it focuses on acoustic features rather than audio features for modeling purposes. The authors report superior performance on the Multimodal Corpus of Sentiment Intensity dataset(MOSI) and Multimodal Opinion Utterances Dataset(MOUD) as compared to the state of the art.

The paper by Li, Rzepka, Ptaszynski, and Araki [31] reports on sentiment classification on Weibo developed on the basis of a custom-made Internet slang and emoticon lexicon derived from Weibo posts. The paper experiments with different parametric and non-parametric approaches to show the effectiveness of their features for capturing humor, especially on the cases which are harder to classify as either positive or negative.

Last but not the least, Sun et. al [72] presented their pre-published work on converting a sentiment classification problem to image classification, through a method they call Super Characters which encodes each observation as an image, and then applies image processing approaches for sentiment classification. Given the pictogram nature of many widely-spoken languages, perhaps it is not surprising that Super Characters consistently outperforms other methods for sentiment classification and topic classification on datasets in four different languages – Chinese, Japanese, and Korean; however, Super Characters also reports a good performance on sentiment analysis on an English dataset of Amazon reviews.

3.4 CL-Aff Shared Task

Eleven teams participated in Task 1 of the inaugural CL-Aff Shared Task AAAI-19 and out of those, five attempted Task 2. The best performing systems were submitted by The University of British Columbia, Canada [59], Arizona State University, USA [65], and the International Institute for Information Technology Hyderabad, India [73]. The Shared Task details are archived on Git [10] and the

[10] https://github.com/kj2013/claff-happydb

complete dataset is indexed on Harvard Dataverse [11]. Shared Task participants showed creativity and ingenuity in modeling the problem in different vector spaces and enriching their training data with external resources. We believe that the widespread adoption of neural approaches for modeling Agency and Sociality and the stupendous performance even on the modest size of the dataset, are an indicator of the swift improvements happening in the field of deep learning for text. In the future, we plan to release other resources complementary to the challenges of modeling affect and emotion language from language.

4 Related Workshops

There is a growing number of workshops and conferences related to affective computing which points to the importance of the research problem at hand, as well as the timeliness of this workshop for the AI community. The following workshops focused mainly on text analysis, sentiment, and subjectivity of the text content:

- SENTIRE series: The workshop on Sentiment Elicitation from Natural Text for Information Retrieval and Extraction has been a continuing series for the past few years at ICDM [12]. The organizers of this workshop series are part of the program committee for the proposed workshop.
- WASSA: The workshop on Computational Approaches to Subjectivity, Sentiment & Social Media Analysis is a workshop series that concentrates on sentiment analysis in text and looks at various aspect–based and subjectivity analysis of text in that context. The workshop has been a popular workshop at top NLP conferences such as EMNLP, ACL, and NAACL in recent years [13]. The organizers of this workshop series as well are a part of the program committee of this proposed workshop.

The following workshops focused on the multi-modal, sensory data in their analysis. Text and language analysis is however not the focus of these workshops. This makes the AAAI Workshop on Affective Content Analysis rather unique in its pitch to bring the two communities together.

- The first workshop on Affective Computing (IJCAI 2017) concentrates on measuring human affects based on sensors and wearable devices.
- 1st Workshop on Tools and Algorithms for Mental Health and Wellbeing, Pain, and Distress (MHWPD)
- Multimodal Emotion Recognition Challenge (MEC 2017) @ 2018 Asian Conference on Affective Computing and Intelligent Interaction (AACII)

Other current relevant events include ACII[14], HUMANAIZE[15], and NLP+CSS[16].

[11] DOI:10.7910/DVN/JZAS66; https://goo.gl/3rcZqf
[12] http://sentic.net/sentire/
[13] http://optima.jrc.it/wassa2017/
[14] http://acii2017.org/
[15] http://st.sigchi.org/publications/toc/humanize-2017.html
[16] https://sites.google.com/site/nlpandcss/nlp-css-at-acl-2017

5 Outlook

This workshop received a promising number of submissions and generated a lot of interest from scholars and industry. The response to the Shared Task was also successful at identifying a community of researchers and a variety of resources for affect analysis in text. The program comprising interdisciplinary keynotes, original research presentations, a poster session and a Shared Task has proven to be a successful and agile format. We will continue this multi–disciplinary workshop in an attempt to establish the space of computational approaches for affective content analysis.

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