Editorial for the 3^{rd} AAAI-20 Workshop on Affective Content Analysis

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Abstract. AffCon2020, the third AAAI Workshop on Affective Content Analysis @ AAAI-20, focused on interactive affective content, i.e., analysis of emotions, sentiments, and attitudes in textual, visual, and multimodal content for applications in psychology, consumer behavior, language understanding, and computer vision especially in conversational content. It included the second CL-Aff Shared Task on modeling self-disclosures. The program comprised keynotes, original research presentations, a poster session, and presentations by the Shared Task winners.

1 Introduction

The third Affective Content Analysis workshop AffCon@AAAI-20 was aimed at engaging the Artificial Intelligence (AI) and Machine Learning (ML) community around the open problems in affective content analysis and understanding. The theme this year was Interactive Affective Responses and focused on aspects of affect in reactions and conversations. The field of 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. [4]

The workshop included the second *CL-Aff Shared Task: Get it #OffMyChest* on modeling interactive affective responses. It focused on the psycholinguistic and semantic characteristics of written accounts of casual and confessional conversations. The task was to predict labels for Disclosure and Supportiveness for sentences based on a small labeled and large unlabeled training data. Six teams completed this shared task.

[4] For the full Program Committee list, see https://sites.google.com/view/affcon2020/committees

 In: N. Chhaya, K. Jaidka, J. Healey, L. H. Ungar, A. Sinha (eds.): Proceedings of the 3rd Workshop of Affective Content Analysis, New York, USA, 07-FEB-2020, published at http://ceur-ws.org

2 Workshop Topics and Format

Presentations at the workshop featured psycholinguists, computer science researchers, and experts in marketing science. Topics included new approaches that address open problems such as deep learning for affect analysis, leveraging traditional affective computing (multimodal datasets), privacy concerns in affect analysis, and inter-relationships between various affect dimensions. These fall under the broad topics of interest of the workshop:

- Deep learning-based models for affect modeling in content (image, audio, and video)
- Psycho-demographic profiling
- Affective and Cognitive Content Measurement in Text
- Affect in communication
- Affectively responsive interfaces
- Affective human-agent, -computer, and -robot interaction
- Mirroring affect
- Affect-aware text generation
- Measurement and evaluation of affective content
- Consumer psychology at scale from big data
- Modeling consumer's affective reactions
- Affect lexica for online marketing communication
- Affective commonsense reasoning
- Multimodal emotion recognition and sentiment analysis
- Computational models for consumer behavior
- Psycho-linguistics, including stylometrics and typography
- Computational linguistics for consumer psychology

3 Overview of the papers

The workshop featured five keynote talks, three paper presentations, and two poster sessions. 38 papers were submitted to the workshop, 6 of which were Systems for the CL-Aff shared task. Finally, 4 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 an invited talk.

The following sections briefly describe the keynote and sessions.

3.1 Keynotes

The first keynote by Prof. Louis-Philippe Morency from CMU was about Multimodal AI, specifically around understanding human-computer interactions and dynamics. The talk started with laying down a foundation around human-agent (computer) interactions and the role of affective interactions in that setup. Further, he discussed methods of modeling multiple aspects of human communication dynamics, in the context of applications in healthcare (depression, PTSD, suicide, autism), education (learning analytics), business (negotiation, interpersonal skills) and social multimedia (opinion mining, social influence).

The next speaker, Dr. Daniel McDuff from Microsoft AI, focused on Building Intelligent and Visceral Machines. The talk covered methods for physiological and behavioral measurement via ubiquitous hardware and then detailed the state-of-the-art approaches for synthesizing behavioral signals. The speaker led with examples of new human-computer interfaces and autonomous systems that leverage behavioral and physiological models, including affect-aware natural language conversation systems, cross-domain learning systems, and vehicles with intrinsic emotional drives. This talk also included a discussion on ethics in the context of affect-aware machines.

Dr. Natasha Jaques, from Google Brain, presented reinforcement learning-based methods leveraged to generate affective dialogues. The methodology presented here was a smart application of applying RL by codifying soft concepts such as feelings and affect. The method leveraged transfer learning to fine-tune a pre-trained dialog model with human feedback using reinforcement learning, and shows how learning from cues like a user's sentiment is more effective than relying on manual labels. These techniques were applied to applications that learn novel conversational rewards, including reducing the toxicity of language generated by the model.

The next session focused on the marketing science perspective of interactions. Prof. Tom Novak and Prof. Donna Hoffman from George Washington University presented a machine learning-based approach in the context of IoT and real-world data. They presented a computational approach that enabled operationalization and visualization of an assemblage theory interpretation of the emergence of automation practices in the Internet of Things. Their approach created a representation of the possibility space of automation assemblages that revealed the boundaries of territorialized automation practices and used this representation as a basis for qualitative analysis, theory development, and estimates of future growth. Extending these methodologies towards affective interactions is an exciting research space. Their keynote was followed by an invited talk from Alain Lemaire from the University of Columbia, who presented his work with Prof. Netzer on linguistic matching of products and consumers. Their empirical analysis suggests that preferences for products can be inferred from the similarity between prospective customers' linguistic style, as well as the language used by other customers to describe a product.

Prof. Robert Kraut, from CMU, presented the final keynote. Dr. Kraut contributed a social psychology perspective to the discussion of interactive affect, covering aspects of social agency and support in support groups. An automated analysis that studied the interactions and dependency patterns in support groups was discussed. An insightful study around understanding how the language in these sites influences how long people stay, the support they receive, and their satisfaction with it. These findings form the basis of methods of interventions to better match support providers with support recipients in both online and in-person support groups environments.

3.2 Papers:

The workshop included 4 full paper presentations and 4 posters. Lin et al. [40] presented their work on context-dependent models for facial expression prediction. Their method aimed to predict expressiveness from visual signals. The models beat baselines and perform at par with human annotations in terms of correlation with the ground truth.

Schoene et al. [75] presented their work on a bidirectional LSTM-based model for Fine-grained emotion classification in Tweets. Their approach showed that a dilated Bi-LSTM with attention achieved state-of-the-art performances beating automated baselines for multiple datasets. The method also outperforms human benchmarks for the emotion classification task.

Fong and Kumar [26] presented an interesting paper based on a hierarchical approach for emotion classification. They present baseline models for both coarse and fine-grained emotion classification. This paper presented a novel 24-way classification scheme for emotion classes. The results showed that the proposed models outperform other baselines across various classes.

Chen et al. [13] presented a fusion-based approach for multi-feature, multimodal sentiment analysis. Their approach combined audio and text features for sentiment classification. They report state-of-the-art results on the IEMOCAP database for multimodal emotion recognition.

3.3 Posters

Four posters were accepted to the workshop. Two of these posters leveraged audio / music data for affective analysis [25,12], Xu et al. [93] modeled customer needs using sentiment based model, and Bara et al. [2] presented an approach for stress detection using multi-modal data.

3.4 CL-Aff Shared Task

Another highlight of the workshop was the 2nd Computational Linguistics Affect Understanding (CL-Aff) Shared Task on modeling interactive affective responses. A new dataset, titled the OffMyChest dataset, was released alongwith two complementary challenges to model disclosure and supportive behavior in social media discussions. Six teams participated in the task. An overview of the approaches and the results is provided as a part of this proceedings [32]. The system approaches were presented as a part of the poster session and are included in this proceedings volume [74,31,83,58,1,92].

4 Related Workshops

Many workshops and conferences are now exploring the problems around affective computing. This suggests the increasing importance of the research problem and 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 [5]. 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 [6]. The organizers of this workshop series as well are a part of the program committee of this proposed workshop.

The following workshops focused on multimodal 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 affect 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[7], HUMANAIZE[8], and NLP+CSS[9].

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.

Acknowledgments

We want to thank Adobe Research for their generous funding, which made this workshop possible. We thank our program committee members who did an ex-

[5] http://sentic.net/sentire/
[6] http://optima.jrc.it/wassa2017/
[7] http://acii2017.org/
[8] http://st.sigchi.org/publications/toc/humanize-2017.html
[9] https://sites.google.com/site/nlpandcss/nlp-css-at-acl-2017

cellent job of reviewing the submissions. All PC members are documented on the AffCon-19 website[10].

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