Emotion Analysis from Texts
(Tutorial Proposal)

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Abstract

Emotion analysis in text is an area of research that encompasses a set of various NLP tasks, including classification and regression settings, as well as structured prediction tasks like role labeling or stimulus detection. It is well-grounded in emotion psychology, which also influences the methodological NLP work. In this tutorial, we provide an overview on emotion psychology, relevant existing resources for emotion analysis, and classification methods. We further discuss appraisal theories and how events can be interpreted regarding their presumably caused emotion and further briefly introduce emotion role labeling. In addition to these technical topics, we discuss the societal impact, provide ethical considerations, and give an overview on open topics in the field.

1 Description and Relevance

Automatic emotion detection in texts has been gaining popularity since 2010's (Acheampong et al., 2020). The systems for automatic emotion detection are often used for social media and public opinion analysis, e.g., with respect to climate change (Loureiro and Alló, 2020), or elections (Anstead and O'Loughlin, 2014). Automatic emotion detection systems are also envisioned to have an important role in building empathetic chatbots and virtual agents (Paiva et al., 2017; Rashkin et al., 2019; Lin et al., 2019b; Shin et al., 2019; Lin et al., 2019a; Ma et al., 2020). More importantly, emotion analysis could be used to aid suicide prevention (Pestian et al., 2012; Desmet and Hoste, 2013), and early depression detection (Deshpande and Rao, 2017).

In the computational linguistics (CL) research community, the most commonly used emotion models are Ekman's model (Ekman and Friesen, 1981) consisting of six basic emotions (*anger*, *disgust*, *fear*, *joy*, *sadness*, and *surprise*), and Plutchik's model (Plutchik, 1982), which is commonly used focusing on eight primary emotions (*anger*, *anticipation*, *disgust*, *fear*, *joy*, *sadness*, *surprise*, and *trust*). However, some studies use only certain subsets of those emotions (e.g., Brynielsson et al., 2014), some use different emotion frameworks (Demszky et al., 2020), a customized emotion set (e.g., Mohammad et al., 2015; Bostan et al., 2020; Huguet Cabot et al., 2021), attitudes (Neviarouskaya et al., 2010), or appraisals (Troiano et al., 2023). Since 2005, over 15 datasets manually annotated for emotions has been compiled and made freely available. The majority of datasets is in English, but they cover a variety of domains and text types: Twitter data (Schuff et al., 2017; Mohammad et al., 2015); personal reports on emotional events (Scherer and Wallbott, 1994; Troiano et al., 2019); sentences from fairy tales (Alm et al., 2005); daily dialogs from websites for English language learners (Li et al., 2017); dialog utterances from the television sitcom Friends (Hsu et al., 2018); movie subtitles (Öhman et al., 2020); news headlines (Bostan et al., 2020; Strapparava and Mihalcea, 2007); and Reddit comments (Demszky et al., 2020; Huguet Cabot et al., 2021). The XED dataset (Öhman et al., 2020), a manually annotated dataset of movies subtitles in English and Finish has been extended to 35 further languages by annotation projection to the parallel sentences in those languages.

From the computational perspective, the research community has used a wide range of approaches for emotion detection and classification, e.g., traditional machine learning approaches that use emotion dictionaries (Mohammad et al., 2015), linear classifiers with various lexical, syntactic, semantic, and structural features (Alm et al., 2005), maximum entropy classifiers with bag-of-words as features (Bostan and Klinger, 2018), support vector machines and naïve Bayes classifiers with various lexical, syntactic, and semantic features (Brynielsson et al., 2014), CNN-based classifiers (Hsu et al., 2018), BERT-based classifiers (Demszky et al., 2020; Öhman et al., 2020), multi-task learning (Huguet Cabot et al., 2021), zero-shot learning (Plaza-del Arco et al., 2022; Gebremichael Tesfagergish et al., 2022), and few-shot learning (Guibon et al., 2021). Given that different architectures were tested on different domains, text types, and class types and distributions, it is not clear which models should be considered state of the art. Commercial emotion analysis models commonly use either dictionary-based approaches (due to their domain customisation capabilities which do not require large amounts of labelled training data) or BERT-based models (due to their domain-agnostic adaptation capabilities in the case of sufficient amounts of labelled training data).

Since 2010's, CL research community has been exponentially increasing the effort in building models for recognising and discerning among Ekman's or Plutchik's basic emotions in texts (Acheampong et al., 2020), and building manually annotated datasets, despite of studies in emotion psychology which suggested that detecting emotions in text is difficult and unreliable (Plutchik, 2001; Lang, 2010). The CL studies have pointed out several challenges in emotion annotation in texts: missing context in short utterances (Öhman et al., 2020; Mohammad, 2012), non-literal meaning (Mohammad, 2012), different perspectives one may take, i.e., the reader's, writer's, or text's (Buechel and Hahn, 2017; Alm et al., 2005), and high subjectivity of the task (low inter-annotator agreements were found even among trained annotators (Alm et al., 2005; Schuff et al., 2017; Štajner, 2021)).

Despite the challenges noted in CL and psychological literature, many tools for emotion analysis are available without a thorough description of challenges and failure modes, e.g., Text2emotion[1] and NRCLex[2] Python libraries. A large number of for-profit companies offer emotion analysis from texts, either using pre-trained models, or customised models trained on clients' data, e.g., BytesView[3], Komprehend[4], IBM Watson Natural Language Understanding.[5] When using the paid emotion analysis APIs, the identification of failure modes on specific datasets or in specific applications, the risk of unintended harms and other ethical considerations are usually shifted to the company or the user of APIs. Those tasks then become extremely difficult given that companies that offer paid APIs do sometimes not disclose the model specifications and datasets the models were trained on.

This tutorial has several goals. First, it provides an overview of most commonly used emotion models and the background in psychology, their limitation and challenges from a psychological perspective as well as from computational linguistics/natural language processing perspective. Second, it provides an extensive overview of freely available emotion analysis datasets, their annotation strategies and limitations. Third, it provides an extensive overview and critical comparison of NLP models used for emotion analysis from texts, ranging from traditional machine learning classifiers based on emotion dictionaries to transformer-based classification systems and zero-shot and few-shot learning models. Finally, this tutorial aims at raising awareness about various ethical issues concerning emotion analysis and the still present challenges in emotion analysis of texts (the absence of standardized annotation and evaluation procedures, common failure modes, etc.) which need to be taken into account when using emotion analysis models in real-world applications to avoid unintended harms.

To provide the tutorial participants with a better understanding of the challenges in emotion analysis and help them get started with developing novel models for emotion analysis, we will implement (at the end of the second part of the tutorial) a small annotation exercise.

2 Type: cutting-edge

The first part of the tutorial is an introduction to emotion psychology and the use cases of emotion analysis. The second and third part of the tutorial, however, cover cutting-edge NLP research on emotion analysis.

3 Target Audience

This tutorial is well-suited for various audiences: junior and senior researches working on emotion annotation and evaluation of emotion detection models; junior and senior researches working on novel models for emotion analysis, especially those using deep-learning paradigms; industry practition-

[1] https://pypi.org/project/text2emotion/
[2] https://pypi.org/project/NRCLex/
[3] https://www.bytesview.com/emotion-analysis
[4] https://komprehend.io/emotion-analysis
[5] https://www.ibm.com/cloud/watson-natural-language-understanding

ers who wish to better understand limitations of publicly available emotion analysis tools and models. There are no prerequisites for attending, although to support a complete understanding of the discussion about strengths and limitations of different computational models, a basic knowledge of commonly used non-neural and neural classifiers is recommended.

4 Tutorial Structure

This tutorial contains three thematic parts, each to be covered in a one-hour time slot. The first part introduces emotion models, findings of relevant psychological studies, and use cases. The second part focuses on existing datasets, identified annotations challenges, and strengths and weaknesses of the computational models which have been proposed so far for emotion classification. The third part covers the tasks of emotion role labeling and stimulus detection as well as the interpretation of events with appraisal theories. Further, it discusses some less commonly discussed but still relevant topics, open questions in emotion analysis from texts, relatedness to other NLP tasks, and ethical considerations for emotion analysis.

Part 1: Foundations

- Emotion theories in psychology
- Emotion recognition reliability in vision and language and what we can expect in NLP
- Use cases and social impact

Part 2: Coarse-grained Emotion Analysis

- Emotion classification resources
- Emotion intensity prediction resources
- Non-neural models
- Multi-task and transfer-based models
- Zero-shot and few-shot learning for emotion classification
- Interactive annotation exercise with data by participants

Part 3: Fine-grained Emotion Analysis and Further Topics

- Event evaluation-based approaches (OCC model and appraisals)
- Emotion role labeling and stimulus/cause detection
- Open challenges in emotion analysis
- Relation to other NLP tasks (including personality profiling and hate speech detection)
- Ethical Considerations

5 Other People's Work

More than 90% of the work cited is not our work.

6 Diversity Considerations

Data. We will emphasize multilingual datasets and approaches wherever possible, e.g., the work of Öhman et al. (2020) who extended the manually annotated datasets to 35 other languages by annotation projection to the parallel sentences in those languages and showed that such projections lead to comparable classification results. We will cover a wide range of domains as mentioned in Section 1.

Instructors. The instructors come from different demographic groups. The tutorial is structured in a way that it is relevant for both junior and senior researches, as well as for researches from both academia and industry.

7 Reading List

Although no particular prior knowledge is necessary for attending the tutorial, we recommend the attendees which are new to the emotion analysis to read the following works from the references section:

- Peter J. Lang. 2010. Emotion and motivation: Toward consensus definitions and a common research purpose. Emotion review 2, 3:229–233.
- Robert Plutchik. 2001. The nature of emotions: Human emotions have deep evolutionary roots, a fact that may explain their complexity and provide tools for clinical practice. American scientist 89, 4:344–350.
- Laura Ana Maria Bostan and Roman Klinger. 2018. An analysis of annotated corpora for emotion classification in text. In Proceedings of the 27th International Conference on Computational Linguistics, pages 2104–2119.
- Emily Öhman, Marc Pàmies, Kaisla Kajava, and Jörg Tiedemann. 2020. XED: A multilingual dataset for sentiment analysis and

emotion detection. In Proceedings of the 28th International Conference on Computational Linguistics, pages 6542–6552.

8 Instructors' Research Interests and Areas of Expertise

Sanja Štajner has over 13 years of research experience across academia and industry on various psycholinguistic topics in NLP. The last four years, she has led and participated in industry-oriented projects that combined psychology and NLP focusing on sentiment analysis, emotion detection, personality modelling, and mental health assessment. Sanja served as a COLING 2018 area chair for psycholinguistics and cognitive modelling track, and an ACL 2022 demo chair. She has experience as tutorial presenter (COLING 2018, AIST 2018, RANLP 2017) for international audiences and as a lecturer at Masters and PhD levels.

Roman Klinger is senior lecturer at Stuttgart University, where he teaches courses on Emotion Analysis since 2016 (see `https://www.emotionanalysis.de/`). He has been principal investigator on several externally funded projects with focus on emotion analysis. Roman served as senior area chair for sentiment analysis and argumentation mining at ACL 2022 and EACL 2021, and is senior area chair for language resources and evaluation at EACL 2023. He is also action editor of ACL Rolling Review 2021–2022. He was organizer of the WASSA workshop (on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis) in 2018, 2019, and 2022.

9 Audience Size

Due to the increased interest in emotion analysis in recent years, we expect 50-80 attendees.

10 Venues

If held online, any of the venues is suitable. If held in person, due to the travel costs, the preferred venue is EACL. Thematically, EACL and ACL are better suited than EMNLP. The tutorial aligns with the special theme of the ACL conference.

11 Special Requirements: none

12 Tutorial Materials

All tutorial materials will be made publicly available and can be shared.

13 Ethics Statement

One of the main goals of the tutorial is to raise awareness about open challenges in emotion analysis which can lead to possible unintended harms and ethical issues with models commonly used for emotion analysis in real-world applications.

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