Experiencer-Specific Emotion and Appraisal Prediction

Maximilian Wegge, Enrica Troiano, Laura Oberländer and Roman Klinger

Institut für Maschinelle Sprachverarbeitung, University of Stuttgart

{firstname.lastname}@ims.uni-stuttgart.de

Abstract

Emotion classification in NLP assigns emotions to texts, such as sentences or paragraphs. With texts like "I felt guilty when he cried", focusing on the sentence level disregards the standpoint of each participant in the situation: the writer ("I") and the other entity ("he") could in fact have different affective states. The emotions of different entities have been considered only partially in emotion semantic role labeling, a task that relates semantic roles to emotion cue words. Proposing a related task, we narrow the focus on the experiencers of events, and assign an emotion (if any holds) to each of them. To this end, we represent each emotion both categorically and with appraisal variables, as a psychological access to explaining why a person develops a particular emotion. On an event description corpus, our experiencer-aware models of emotions and appraisals outperform the experiencer-agnostic baselines, showing that disregarding event participants is an oversimplification for the emotion detection task.

1 Introduction

Computational emotion analysis from text includes various subtasks, with the most prominent one being emotion classification or regression. Its goal is to assign an emotion representation to textual units, and the way this is done typically depends on the domain of the data, the practical application of the task, and the psychological theories of reference: emotions can be modelled as discrete labels, in line with theories of basic emotions (Ekman, 1992; Plutchik, 2001), as valence—arousal value pairs that define an affect vector space where to situate emotion concepts (illustrated, e.g., by Posner et al., 2005), or as appraisal spaces that correspond to the cognitive evaluative dimensions underlying emotions¹ (Scherer, 2005; Smith and Ellsworth, 1985).

Irrespective of the adopted representations, most work in the field detects emotions from a single perspective – either to recover the emotion that the writer of a text likely expressed (e.g., with respect to emotion categories and intensities (Mohammad et al., 2018), and cognitive categories (Hofmann et al., 2020)), or to predict the emotion that the text elicits in the readers (e.g., using news articles, Strapparava and Mihalcea, 2007; Bostan et al., 2020). Only a few approaches combine or compare the reader's with the writer's perspective (Buechel and Hahn, 2017, i.a.). However, none of them looks at the perspectives of the *participants* in events (both mentioned or implicit) as described by a text.

Focusing on such perspectives separately is essential to develop an all-round account of the affective implications that events have. It would emphasize how the facts depicted in text are amenable to different "emotion narratives", by pushing one or the other perspective in the foreground. For instance, a possible interpretation for the sentence "As the waiter yelled at her, the expression on my mother's face made all the staff look repulsed", could be: "my mother"—sadness, "the waiter"—anger, and "the staff"—disgust. There, one entity is responsible for an event (screaming), one is influenced by it, and the third is affected by the emotion emerging in the other (the facial expression, which can be seen as an event in itself).

Our goal is close to emotion role labeling, a special case of semantic role labeling (SRL) (Mohammad et al., 2018; Kim and Klinger, 2018). SRL addresses the question "Who did What to Whom, Where, When, and How?" (Gildea and Jurafsky, 2000), emotion SRL asks "Who feels what, why, and towards whom?" (Kim and Klinger, 2018), mainly to detect causes of emotion-eliciting events (Ghazi et al., 2015) for certain entities. Here, we tackle a variation of this question, namely, "Who feels what and under which circumstances?". The circumstances refer to the explanation pro-

¹They are similar to a valence–arousal space, but the dimensions correspond to evaluations of events (i.e., appraisals) that underlie a certain emotion.

vided by appraisal interpretations, another novelty that we contribute to the emotion SRL panorama. Appraisal-based emotion representations capture entity-specific aspects that lead to an emotion, as they describe the subjective qualities that an individual sees in events.

We propose a method for experiencer-specific emotion and appraisal analysis that bridges emotion classification and semantic role labeling. Given texts that describe events and that include annotations for all participants, we assign an emotion and an appraisal vector to each potential emoter. Our proposal is computationally simpler than creating a full graph of relations between causes and entities, as is normally done in (emotion) SRL. Yet, its fine-grained focus on event participants is beneficial over traditional classification- and regressionbased approaches: by predicting an emotion and scoring multiple appraisals for each entity, our model strongly outperforms text-level baselines. Thus, the results demonstrate that assigning one emotion to the entire instance, or multiple emotions without considering for whom they hold, is a simplification of the emotional import of the text.

2 Related Work

In natural language processing, emotions are usually represented as discrete names following theories of basic emotions (Ekman, 1992; Plutchik, 2001), or as values of valence and arousal (Russell and Mehrabian, 1977). Computational models based on such representations have been applied to many text sources, including Reddit comments (Demszky et al., 2020) and tales (Alm et al., 2005), but also to resources created as part of psychological research. An example is the ISEAR corpus. It consists of short reports collected in lab (Scherer and Wallbott, 1997), instructing participants to describe events that caused in them a certain emotion. A similar collection practice was adopted by Troiano et al. (2019). In their enISEAR, crowdworkers completed sentences like "I felt [EMOTION NAME] when ..." for seven emotion names.

The emotions of entities are considered in emotion SRL, whose goals comprise the recognition of emotion cue words, emotion experiencers/emoters and descriptions of emotion causes and targets (Mohammad et al., 2018; Bostan et al., 2020; Kim and Klinger, 2018; Campagnano et al., 2022, i.a.). Yet, most work focused on detecting causes (i.e., emotion-triggering events), and less on other se-

Emotion Class	# inst.	# exp.
anger	259	336
disgust	73	87
fear	173	220
joy, pride, contentment	181	265
no emotion	223	269
other, anticipation, hope,		
surprise, trust	102	117
sadness, disappointment,		
frustration	320	423
shame, guilt	282	325
total	720	1329

Table 1: Number of instances and experiencer spans annotated for each emotion. Non-bold emotion names are concepts in the x-enVENT data that we merge with bold emotion names in our experiments.

mantic roles (Russo et al., 2011; Chen et al., 2018, 2010; Cheng et al., 2017, i.a.).

The gap between entity-specific emotion analysis and emotion SRL was partially filled in by Troiano et al. (2022). They aimed at better understanding the readers' attempts to interpret the experience of the texts' authors. They post-annotated instances from enISEAR with emotions and 22 appraisal concepts, both for the writer and all other event participants mentioned in the text. The appraisal variables include evaluations of events, as they were likely conducted by the event experiencers, including if authors felt responsible, if they needed to pay attention to the environment, whether they found themselves in control of the situation, and its pleasantness (see Table 1 in their paper for explanations of the variables). However, their work was limited to corpus creation and analysis, and did not provide any modeling of appraisals or emotions in an emotion experiencer-specific manner. Therefore, it is not clear whether a simplifying assumption that all entities experience the same emotion or an actual entity-specific model performs practically better. We address this concern and show that experiencer-specific modeling is beneficial.

Finally, our work is related to structured sentiment analysis (Barnes et al., 2021), in which opinion targets, their polarity, but also an opinion-holding (or expressing) entity is to be detected. Most studies focused on sentiment targets and aspects (Brauwers and Frasincar, 2021), but there are also some that aim at detecting the opinion holder (Kim and Hovy, 2006; Wiegand and Klakow, 2011; Seki, 2007; Wiegand and Klakow, 2012, i.a.).

		Annotation		
Model	Input instance	Emotion	Appraisal	
EXP	⟨exp⟩WRITER⟨/exp⟩ I felt bad for him	{guilt}	$\overline{(5,1,1,\ldots)}$	
	WRITER I felt bad \dots for $\langle \exp \rangle him \langle / \exp \rangle$	{sadness}	$(1,3,1,\ldots)$	
TEXT	WRITER I felt bad for him	{guilt, sadness}	$\overline{(3,2,1,\ldots)}$	

Table 2: Example representation at training time for the EXP model and the TEXT baseline for the instance "WRITER I felt bad for not being there for him".

3 Methods and Experimental Setting

Model. We model the task of experiencer-specific emotion analysis as a classification of instances which consist of experiencers e in the context of a text $\mathbf{t}_e = (t_1, \dots, t_n)$. There can be multiple experiencers in one text, therefore $\mathbf{t}_e = \mathbf{t}_{e'}$ is possible. Each experiencer consists of a corresponding token sequence (t_i, \dots, t_j) $(1 \le i, j, \le |\mathbf{t}_e|)$, a set of emotion labels $E_e \in \{\text{anger}, \text{fear}, \text{joy}, \dots\}$, and a 22-dimensional appraisal vector $\mathbf{a}_e \in [1; 5]^{22}$.

To predict \mathbf{a}_e and E_e for each experiencer e with the help of \mathbf{t}_e , we use as input a positional indicator-encoding of the experiencers in context (inspired by Zhou et al., 2016). The writer is encoded with an additional special token $t_o = \text{WRITER}$. We refer to this experiencer-specific model as EXP.

Baseline. We compare this model to a baseline in which we simplify the experiencer-specific classification as text-level classification. During training, we assign the text \mathbf{t} the union of all emotion labels of all contained experiencers, namely $E_{\mathbf{t}} = \bigcup_{e, \mathbf{t}_e = \mathbf{t}} E_e$. Analogously, the aggregation of the appraisal vectors is the centroid of all experiencers in one text: $\mathbf{a}_{\mathbf{t}} = \frac{1}{|\{e|\mathbf{t}_e = \mathbf{t}\}|} \sum_{e, \mathbf{t}_e = \mathbf{t}} \mathbf{a}_e$. We refer to this baseline model as TEXT(-based prediction). Table 2 examplifies the input representations.

Data Preparation. We use the x-enVENT data set (Troiano et al., 2022) for our experiments. It consists of 720 event descriptions, mainly from the enISEAR corpus (Troiano et al., 2019), which we split into 612 instances for training and 108 instances for testing (stratified). Each text has been annotated by four annotators and adjudicated to span-based experiencer annotations with a multilabel emotion classification and an appraisal vector. We merge infrequent emotion classes from the original corpus. Table 1 shows the label distribution.

	TEXT			EXP			
Emotion Class	P	R	$\overline{F_1}$	P	R	$\overline{F_1}$	ΔF_1
anger	40	82	54	60	80	68	+14
disgust	50	93	65	60	80	69	+4
fear	44	86	58	53	71	61	+3
joy	55	70	62	61	77	68	+6
no emotion	29	80	42	51	80	62	+20
other	11	10	10	14	10	12	+2
sadness	47	90	62	62	93	74	+12
shame	34	89	49	48	85	61	+12
Macro avg.	39	75	51	51	72	60	+9
Micro avg.	40	79	53	55	78	64	+11

Table 3: Emotion classification results of the TEXT-based baseline which is not informed about experiencer-specific emotions with our emotion experiencer-specific model Exp.

Implementation. We fine-tune Distil-RoBERTa (Liu et al., 2019) based on the Hugging Face implementation (Wolf et al., 2020). For both the emotion classification and the appraisal regression tasks, we follow a multi-task learning scheme. All emotion categories are predicted jointly by one model with a multi-output classification head, analogously with a regression head for the appraisal vector. The appendix contains implementation details.²

Evaluation. We evaluate performance by calculating experiencer-specific F_1 scores for emotion classification and Spearman's ρ for appraisal regression. In the TEXT baseline, we project the decision for the text to each experiencer that it contains.

4 Results

Quantitative Evaluation. Tables 3 and 4 show the results. For emotion classification, we report precision, recall, and F₁ measures for the baseline TEXT and the experiencer-specific predictions by EXP in Table 3. EXP substantially outperforms TEXT in terms of F₁ score. This trend holds across all emotion categories, as a result of an increased precision, which is intuitively reasonable, because the EXP model learns to distribute the emotions that are contained in a text to individual experiencers, while the TEXT baseline distributes all emotions to all experiencers equally, leading to an increased recall. The most substantial improvements are observed for anger (+14), sadness (+12) and shame (+12) as well as for no emotion (+20). These results are in line with the corpus analysis by Troiano

²Our implementation is available at https: //www.ims.uni-stuttgart.de/data/ appraisalemotion.

	TEXT	Exp	
Appraisal Dimension	ρ	ρ	$\Delta \rho$
Suddenness	0.32	0.54	+0.22
Familiarity	0.17	0.37	+0.20
Pleasantness	0.34	0.60	+0.26
Understand	0.24	0.30	+0.06
Goal relevance	0.15	0.33	+0.18
Self responsibility	0.31	0.68	+0.37
Other responsibility	0.33	0.68	+0.35
Situational respons.	0.59	0.68	+0.09
Effort	0.33	0.54	+0.21
Exert	0.97	0.25	-0.72
Attend	0.27	0.41	+0.14
Consider	0.55	0.62	+0.07
Outcome probability	0.14	0.38	+0.24
Expect. discrepancy	0.43	0.54	+0.11
Goal conduciveness	0.47	0.65	+0.18
Urgency	0.20	0.25	+0.05
Self control	0.36	0.64	+0.28
Other control	0.41	0.69	+0.28
Situational control	0.63	0.67	+0.04
Adjustment check	0.39	0.56	+0.17
Internal check	0.47	0.58	+0.11
External check	0.66	0.54	-0.12
Avg.	0.44	0.54	+0.09

Table 4: Appraisal regression results of the TEXT-based baseline and the experiencer-specific model EXP. The average has been calculated via FisherZ-Transformation.

et al. (2022). They found that some emotions are often shared between different experiencers within one text, but others occur in common pairs, namely guilt—anger, no emotion—sadness, guilt—sadness and shame—anger. Noteworthy is the category no emotion, which commonly occurs with all other emotions (Troiano et al., 2022, Figure 4). The performance increase for joy, fear and disgust is less distinct: these emotions are likely shared by all event experiencers.

For the appraisal predictions, we report Spearman's ρ in Table 4. We observe an improved performance prediction across nearly all dimensions. Appraisals that distinguish between who caused the event and who had the power to influence it (self vs. other) show the most substantial improvement, namely self responsibility (+0.37) and self control (+0.28), as well as other responsibility (+0.35) and other control (+0.28). This is reasonable – the self and other are often mutually exclusive. This interaction of appraisals cannot be exploited by purely text-level prediction models. However, if an event is caused by external factors, like situational responsibility (+.09) and situational control (+.04), all experiencers are equally affected by it. The decrease in performance for external check (-0.12) might be explained by the fact that this dimension is often shared between experiencers, rendering the TEXT model sufficiently efficient.

Analysis. We show some examples in Table 5 that highlight the usefulness of EXP over TEXT. Next to the emotion classification annotations and predictions from both models, we show the appraisals of *self responsibility/other responsibility* and *self control/other control*. In each example, the writer is one emotion experiencer. All other experiencers are underlined.

We observe that the TEXT model has a tendency to predict the union of the emotions for all experiencers, but sometimes predicts more additional categories. This is a consequence of the tendency towards high recall predictions of this model. In Example 1, both EXP and TEXT correctly assign the emotions anger, disgust and no emotion, but only EXP distributes them correctly between "Writer" and "The owners" (sadness is wrongly detected by both models). In Example 2, joy is not predicted by TEXT, but correctly assigned to "a group of children" by EXP. EXP further distributes shame and sadness to the correct entities (with a mistake assigning anger and no emotion to "a group of children" as well as anger and fear to "another child"). In Example 3, EXP correctly assigns sadness and shame to "Writer" and sadness and no emotion to "my sister", while TEXT fails to detect no emotion. In Example 4, EXP's prediction of anger and fear (for "our children") could be accepted to be correct despite it not being in line with the gold annotation. EXP further predicts the correct emotions for "Writer" (but makes a mistake assigning joy to "my ex husband"). In Example 5, the emotions of "Writer" are correctly assigned; "my son" is wrongly assigned joy in addition to no emotion (TEXT mistakenly predicts other as well). However, the correctness of this annotation is debatable.

Maximal values for the gold appraisal values for self/other control and self/other responsibility are, in nearly all cases, mutually exclusive across experiencers. The TEXT model is not informed about that and distributes the values across all entities. The EXP model does indeed recover the individual values for the appraisals, but to varying degrees. In Examples 2, 3, and 4, nearly all experiencers receive appraisal values close to the gold annotations. Example 2 appears to be challenging: the writer has a high gold annotation value for *self responsibility* which is not automatically detected. Further, "a

	_
II)	Text
\mathbf{n}	ILLA

- 1 I felt ... working in the street seeing faeces of dogs. <u>The owners</u> should take care of them but are being so lazy and neglected, that is terrible.
- 2 I felt ... when I remember being part of a group of children at school who verbally bullied <u>another child</u>.
- 3 I felt ... when I lost my sister's necklace that I had borrowed.
- 4 I felt ... when my ex husband was hateful towards our children.
- 5 I felt ... when my son was born.

(a) Example Texts

		Gold		TEX	ΚΤ	Ехр	
ID	Experiencer Text	Emotion	Appraisal	Emotion	Appraisal	Emotion	Appraisal
1	Writer The owners	a d no		a d no sa a d no sa		a d sa no	
2	Writer a group of children another child	sh j sh sa		a no sa sh a no sa sh a no sa sh		sh a j no sh a f sa	
3	Writer my sister	sa sh sa no		sa sh sa sh		sa sh sa no	
4	Writer my ex husband our children	a sa a sh sa		a f j no sa sh a f j no sa sh a f j no sa sh		a sa a j sh a f sa	
5	Writer my son	j no		j o no j o no		j j no	

(b) Annotations

Table 5: Examples of EXP and TEXT predictions. a: anger, d: disgust, no: no emotion, o:other, sa: sadness, sh: shame, f: fear, j: joy. The boxes show the appraisal *self responsibility*, *other responsibility*, *self control*, *other control*, with values between \square and \blacksquare .

group of children" receives the same values for the four appraisals. Examples 1/5 are cases in which the appraisal prediction does not work as expected.

5 Discussion and Conclusion

We presented the first approach of experiencerspecific emotion classification and appraisal regression. Our evaluation on event descriptions shows the need for such methods, and that a text-instance level annotation is a simplification.

This work provides the foundation for future research focused on texts in which multiple emotion labels co-occur, including reader/writer combinations or turn-taking dialogues. We propose to integrate experiencer-specific emotion modeling within such settings, for instance in novels, or news articles. It can also enrich the work of emotion recognition in dialogues (Poria et al., 2019): Chains of emotions have been modeled, but not considering mentioned entities.

Our work focused on a corpus that has been annotated specifically for writers' and entities' emotions. There exist, however, also other corpora with

experiencer-specific emotion annotations, namely emotion role labeling resources (Kim and Klinger, 2018; Bostan et al., 2020; Campagnano et al., 2022; Mohammad et al., 2014). In addition to other information, they also provide experiencer-specific emotion labels, though not in such an event-focused context. Still, modeling them following our method needs to be compared to more traditional approaches that aim at recovering the full role labeling graph.

Our approach to encoding the experiencer position in the classifier has been a straightforward choice. Other model architectures (including positional embeddings, Wang and Chen, 2020) might perform better. Another interesting methodological avenue is to model the predictions of multiple experiencers jointly to exploit their relations.

Finally, an open question is how to incorporate information from existing resources that are not labeled with experiencer-specific information. For instance, Troiano et al. (2023) provide appraisal and emotion annotations for many more instances that might be beneficial in a transfer-learning setup.

Acknowledgements

This research is funded by the German Research Council (DFG), project "Computational Event Analysis based on Appraisal Theories for Emotion Analysis" (CEAT, project number KL 2869/1-2).

References

- Cecilia Ovesdotter Alm, Dan Roth, and Richard Sproat. 2005. Emotions from text: Machine learning for text-based emotion prediction. In *Proceedings of Human Language Technology Conference and Conference on Empirical Methods in Natural Language Processing*, pages 579–586, Vancouver, British Columbia, Canada. Association for Computational Linguistics.
- Jeremy Barnes, Robin Kurtz, Stephan Oepen, Lilja Øvrelid, and Erik Velldal. 2021. Structured sentiment analysis as dependency graph parsing. In *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)*, pages 3387–3402, Online. Association for Computational Linguistics.
- Laura Ana Maria Bostan, Evgeny Kim, and Roman Klinger. 2020. GoodNewsEveryone: A corpus of news headlines annotated with emotions, semantic roles, and reader perception. In *Proceedings of the 12th Language Resources and Evaluation Conference*, pages 1554–1566, Marseille, France. European Language Resources Association.
- Gianni Brauwers and Flavius Frasincar. 2021. A survey on aspect-based sentiment classification. *ACM Comput. Surv.* Just Accepted.
- Sven Buechel and Udo Hahn. 2017. Readers vs. writers vs. texts: Coping with different perspectives of text understanding in emotion annotation. In *Proceedings of the 11th Linguistic Annotation Workshop*, pages 1–12, Valencia, Spain. Association for Computational Linguistics.
- Cesare Campagnano, Simone Conia, and Roberto Navigli. 2022. SRL4E Semantic Role Labeling for Emotions: A unified evaluation framework. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 4586–4601, Dublin, Ireland. Association for Computational Linguistics.
- Ying Chen, Wenjun Hou, Xiyao Cheng, and Shoushan Li. 2018. Joint learning for emotion classification and emotion cause detection. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 646–651, Brussels, Belgium. Association for Computational Linguistics.
- Ying Chen, Sophia Yat Mei Lee, Shoushan Li, and Chu-Ren Huang. 2010. Emotion cause detection with linguistic constructions. In *Proceedings of the 23rd*

- *International Conference on Computational Linguistics (Coling 2010)*, pages 179–187, Beijing, China. Coling 2010 Organizing Committee.
- Xiyao Cheng, Ying Chen, Bixiao Cheng, Shoushan Li, and Guodong Zhou. 2017. An emotion cause corpus for chinese microblogs with multiple-user structures. *ACM Trans. Asian Low-Resour. Lang. Inf. Process.*, 17(1).
- Dorottya Demszky, Dana Movshovitz-Attias, Jeongwoo Ko, Alan Cowen, Gaurav Nemade, and Sujith Ravi. 2020. GoEmotions: A dataset of fine-grained emotions. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 4040–4054, Online. Association for Computational Linguistics.
- Paul Ekman. 1992. An argument for basic emotions. *Cognition & emotion*, 6(3-4):169–200.
- Diman Ghazi, Diana Inkpen, and Stan Szpakowicz. 2015. Detecting emotion stimuli in emotion-bearing sentences. In *International Conference on Computational Linguistics and Intelligent Text Processing*, pages 152–165. Springer.
- Daniel Gildea and Daniel Jurafsky. 2000. Automatic labeling of semantic roles. In *Proceedings of the 38th Annual Meeting of the Association for Computational Linguistics*, pages 512–520, Hong Kong. Association for Computational Linguistics.
- Xavier Glorot and Yoshua Bengio. 2010. Understanding the difficulty of training deep feedforward neural networks. In *Proceedings of the Thirteenth International Conference on Artificial Intelligence and Statistics, AISTATS 2010, Chia Laguna Resort, Sardinia, Italy, May 13-15, 2010*, volume 9 of *JMLR Proceedings*, pages 249–256. JMLR.org.
- Jan Hofmann, Enrica Troiano, Kai Sassenberg, and Roman Klinger. 2020. Appraisal theories for emotion classification in text. In *Proceedings of the 28th International Conference on Computational Linguistics*, pages 125–138, Barcelona, Spain (Online). International Committee on Computational Linguistics.
- Evgeny Kim and Roman Klinger. 2018. Who feels what and why? annotation of a literature corpus with semantic roles of emotions. In *Proceedings of the 27th International Conference on Computational Linguistics*, pages 1345–1359, Santa Fe, New Mexico, USA. Association for Computational Linguistics.
- Soo-Min Kim and Eduard Hovy. 2006. Extracting opinions, opinion holders, and topics expressed in online news media text. In *Proceedings of the Workshop on Sentiment and Subjectivity in Text*, pages 1–8, Sydney, Australia. Association for Computational Linguistics.
- Diederik P. Kingma and Jimmy Ba. 2015. Adam: A method for stochastic optimization. In 3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings.

- Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. RoBERTa: A robustly optimized BERT pretraining approach. arXiv:1907.11692.
- Saif Mohammad, Felipe Bravo-Marquez, Mohammad Salameh, and Svetlana Kiritchenko. 2018. SemEval-2018 task 1: Affect in tweets. In *Proceedings of The 12th International Workshop on Semantic Evaluation*, pages 1–17, New Orleans, Louisiana. Association for Computational Linguistics.
- Saif Mohammad, Xiaodan Zhu, and Joel Martin. 2014. Semantic role labeling of emotions in tweets. In *Proceedings of the 5th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis*, pages 32–41, Baltimore, Maryland. Association for Computational Linguistics.
- Robert Plutchik. 2001. The nature of emotions. *American Scientist*, 89(4):344–350.
- Soujanya Poria, Navonil Majumder, Rada Mihalcea, and Eduard Hovy. 2019. Emotion recognition in conversation: Research challenges, datasets, and recent advances. *IEEE Access*, 7:100943–100953.
- Jonathan Posner, James A. Russell, and Bradley S. Peterson. 2005. The circumplex model of affect: an integrative approach to affective neuroscience, cognitive development, and psychopathology. *Development and Psychopathology*, 17(3):715–734.
- James A Russell and Albert Mehrabian. 1977. Evidence for a three-factor theory of emotions. *Journal of research in Personality*, 11(3):273–294.
- Irene Russo, Tommaso Caselli, Francesco Rubino, Ester Boldrini, and Patricio Martínez-Barco. 2011. EMO-Cause: An easy-adaptable approach to extract emotion cause contexts. In *Proceedings of the 2nd Workshop on Computational Approaches to Subjectivity and Sentiment Analysis (WASSA 2.011)*, pages 153–160, Portland, Oregon. Association for Computational Linguistics.
- Klaus R. Scherer. 2005. What are emotions? And how can they be measured? *Social Science Information*, 44(4):695–729.
- Klaus R. Scherer and Harald G. Wallbott. 1997. The ISEAR questionnaire and codebook. Geneva Emotion Research Group.
- Yohei Seki. 2007. Opinion holder extraction from author and authority viewpoints. In *Proceedings of the 30th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval*, SIGIR '07, page 841–842, New York, NY, USA. Association for Computing Machinery.
- Craig A Smith and Phoebe C Ellsworth. 1985. Patterns of cognitive appraisal in emotion. *Journal of personality and social psychology*, 48(4):186–209.

- Carlo Strapparava and Rada Mihalcea. 2007. SemEval-2007 task 14: Affective text. In *Proceedings of the Fourth International Workshop on Semantic Evaluations (SemEval-2007)*, pages 70–74, Prague, Czech Republic. Association for Computational Linguistics.
- Enrica Troiano, Laura Oberländer, and Roman Klinger. 2023. Dimensional modeling of emotions in text with appraisal theories: Corpus creation, annotation reliability, and prediction. *Computational Linguistics*, 49(1):1–71. In print.
- Enrica Troiano, Laura Oberländer, Maximilian Wegge, and Roman Klinger. 2022. x-enVENT: A corpus of event descriptions with experiencer-specific emotion and appraisal annotations. In *Proceedings of The 13th Language Resources and Evaluation Conference*, Marseille, France. European Language Resources Association.
- Enrica Troiano, Sebastian Padó, and Roman Klinger. 2019. Crowdsourcing and validating event-focused emotion corpora for German and English. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 4005–4011, Florence, Italy. Association for Computational Linguistics.
- Yu-An Wang and Yun-Nung Chen. 2020. What do position embeddings learn? an empirical study of pre-trained language model positional encoding. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 6840–6849, Online. Association for Computational Linguistics.
- Michael Wiegand and Dietrich Klakow. 2011. The role of predicates in opinion holder extraction. In *Proceedings of the RANLP 2011 Workshop on Information Extraction and Knowledge Acquisition*, pages 13–20, Hissar, Bulgaria. Association for Computational Linguistics.
- Michael Wiegand and Dietrich Klakow. 2012. Generalization methods for in-domain and cross-domain opinion holder extraction. In *Proceedings of the 13th Conference of the European Chapter of the Association for Computational Linguistics*, pages 325–335, Avignon, France. Association for Computational Linguistics.
- Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Remi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander Rush. 2020. Transformers: State-of-the-art natural language processing. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pages 38–45, Online. Association for Computational Linguistics.
- Peng Zhou, Wei Shi, Jun Tian, Zhenyu Qi, Bingchen Li, Hongwei Hao, and Bo Xu. 2016. Attention-based

bidirectional long short-term memory networks for relation classification. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 207–212, Berlin, Germany. Association for Computational Linguistics.

A Implementation Details.

We fine-tune Distil-RoBERTa (Liu et al., 2019) as implemented in the Hugging Face library³ (Wolf et al., 2020) and leave default parameters unchanged. For both the emotion classification and the appraisal regression tasks, we follow a multitask learning scheme. All emotion categories are predicted jointly by one model with a multi-output classification head, analogously with a regression head for the appraisal vector prediction. The classification head consists of a linear layer with dropout (0.5) and ReLU activation function, followed by a final linear layer with sigmoid activation. For the appraisal regression, the sigmoid activation function in the final layer is replaced by a linear activation. We use binary cross entropy loss in the emotion classifier and mean squared error loss in the appraisal regressor. Both models are trained for 10 epochs without early stopping. We use the Adam optimizer (Kingma and Ba, 2015) with weight decay (0.001) and a learning rate of $2 \cdot 10^{-5}$. The weights of each layer are initialized using the Xavier uniform initialization (Glorot and Bengio, 2010). The hyperparameters and architecture have been decided on via 10-fold cross validation on the training data.