Emotion Recognition under Consideration of the Emotion Component Process Model

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Abstract

Emotion classification in text is typically performed with neural network models which learn to associate linguistic units with emotions. While this often leads to good predictive performance, it does only help to a limited degree to understand how emotions are communicated in various domains. The emotion component process model (CPM) by Scherer (2005) is an interesting approach to explain emotion communication. It states that emotions are a coordinated process of various subcomponents, in reaction to an event, namely the subjective feeling, the cognitive appraisal, the expression, a physiological bodily reaction, and a motivational action tendency. We hypothesize that these components are associated with linguistic realizations: an emotion can be expressed by describing a physiological bodily reaction ("he was trembling"), or the expression ("she smiled"), etc. We annotate existing literature and Twitter emotion corpora with emotion component classes and find that emotions on Twitter are predominantly expressed by event descriptions or subjective reports of the feeling, while in literature, authors prefer to describe what characters do, and leave the interpretation to the reader. We further include the CPM in a multitask learning model and find that this supports the emotion categorization. The annotated corpora are available at `https://www.ims.uni-stuttgart.de/data/emotion`.

1 Introduction

The task of emotion classification from written text is to map textual units, like documents, paragraphs, or sentences, to a predefined set of emotions. Common class inventories rely on psychological theories such as those proposed by Ekman (1992) (*anger*, *disgust*, *fear*, *joy*, *sadness*, *surprise*) or Plutchik (2001). Often, emotion classification is tackled as an end-to-end learning task, potentially informed by lexical resources (see the SemEval Shared Task 1 on Affect in Tweets for an overview of recent approaches (Mohammad et al., 2018)).

While end-to-end learning and fine-tuning of pretrained models for classification have shown great performance improvements in contrast to purely feature-based methods, such approaches typically neglect the existing knowledge about emotions in psychology (which might help in classification and to better understand how emotions are communicated). There are only very few approaches that aim at combining psychological theories (beyond basic emotion categories) with emotion classification models: We are only aware of the work by Hofmann et al. (2020), who incorporate the cognitive appraisal of events, and Buechel et al. (2020), who jointly learn affect (valence, arousal) and emotion classes; next to knowledge-base-oriented modelling of events by Balahur et al. (2012) and Cambria et al. (2014).

An interesting and attractive theory for computational modelling of emotions that has not been used in natural language processing yet is the emotion component process model (Scherer, 2005, CPM). This model states that emotions are a coordinated process in five subsystems, following an event that is relevant for the experiencer of the emotion, namely a *motivational action tendency*, the *motor expression* component, a *neurophysiological, bodily symptom*, the *subjective feeling*, and the *cognitive appraisal*. The cognitive appraisal has been explored in a fine-grained manner by Hofmann et al. (2020), mentioned above. The subjective feeling component is related to the dimensions of affect.[1]

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[1]There exists other work that has been motivated by appraisal theories, but that is either rule-based (Shaikh et al., 2009; Udochukwu and He, 2015) or does not explicitly model appraisal or component dimensions (Balahur et al., 2012;

We hypothesize (and subsequently analyze) that emotions in text are communicated in a variety of ways, and that these different stylistic means follow the emotion component process model. The communication of emotions can either be an explicit mention of the emotion name ("I am angry"), focus on the motivational aspect ("He wanted to run away."), describe the expression ("She smiled.", "He shouted.") or a physiological bodily reaction ("she was trembling", "a tear was running down his face"), the subjective feeling ("I felt so bad."), or, finally, describe a cognitive appraisal ("I wasn't sure what was happening.", "I am not responsible.").

With this paper, we study how emotions are communicated (following the component model) in Tweets (based on the Twitter Emotion Corpus TEC, by Mohammad (2012)) and literature (based on the REMAN corpus by Kim and Klinger (2018)). We post-annotate a subset of 3041 instances with the use of emotion component-based emotion communication categories, analyze this corpus, and perform joint modelling/multi-task learning experiments. Our research goals are (1) to understand if emotion components are distributed similarly across emotion categories and domains, and (2) to evaluate if informing an emotion classifier about emotion components improves their performance (and to evaluate various classification approaches). We find that emotion component and emotion classification prediction interact and benefit from each other and that emotions are communicated by means of various components in literature and social media. The corpus is available at `https://www.ims.uni-stuttgart.de/data/emotion`.

2 Background and Related Work

2.1 Emotion Models

Emotion models can be separated into those that consider a discrete set of categories or those that focus on underlying principles like affect. The model of basic emotions by Ekman (1992) considers anger, disgust, fear, joy, sadness, and surprise. According to his work, there are nine characteristics that a basic emotion fulfills: These are (1) distinctive universal signals, (2) presence in other primates, (3) distinctive physiology, (4) distinctive universals in antecedent events, (5) coherence among emotional response, (6) quick onset, (7) brief duration, (8) automatic appraisal, and (9) unbidden occurrence. His model of the six universal emotions constitutes one of the most popular emotion sets in natural language processing. Yet it might be doubted if this set is sufficient. Plutchik (2001) proposed a model with eight main emotions, visualized on a colored wheel. In this visualization, opposites and distance of emotion names are supposed to correspond to their respective relation.

A complementary approach to categorizing emotions in discrete sets is advocated by Russell and Mehrabian (1977). Their dimensional affect model corresponds to a 3-dimensional vector space with dimensions for pleasure-displeasure, the degree of arousal, and dominance-submissiveness (VAD). Emotion categories correspond to points in this vector space. A more expressive alternative to the VAD model of affect is motivated by the cognitive appraisal process that is part of emotions. The model of Smith and Ellsworth (1985) introduces a set of variables that they map to the principle components of pleasantness, responsibility/control, certainty, attention, effort, and situational control. They show that these dimensions are more powerful to distinguish emotion categories than VAD.

Appraisals are also part of the emotion component process model by Scherer (2005), which is central to this paper. The five components are *cognitive appraisal*, *neurophysiological bodily symptoms*, *motor expressions*, *motivational action tendencies*, and *subjective feelings*. *Cognitive appraisal* is concerned with the evaluation of an event. The event is assessed regarding its relevance to the individual, the implications and consequences it might lead to, the possible ways to cope with it and control it, and its significance according to personal values and social norms. The component of *neurophysiological symptoms* regards automatically activated reactions and symptoms of the body, like changes in the heartbeat or breathing pattern. The *motor expression* component contains all movements, facial expressions, changes concerning the speech, and similar patterns. Actions like attention shifts and movement with respect to the position of the event are part of the *motivational action tendencies* component. Finally, the component of *subjective feelings* takes into account how strong, important, and persisting the felt sensations are. Scherer (2005) argues that it is possible to infer the emotion a person is experiencing by analyzing the set of changes in the five components. Scherer (2009) also points out that computational models must not ignore emotion components.

Rashkin et al., 2018).

2.2 Emotion Analysis in Text

The majority of modelling approaches focuses on the analysis of fundamental emotions (see Alswaidan and Menai, 2020; Mohammad et al., 2018; Bostan and Klinger, 2018) or on the recognition of valence, arousal, and dominance (Buechel and Hahn, 2017). Work with a focus on other aspects of emotions is scarce.

Noteworthy, though this has not been a computational study, is the motivation of the ISEAR project (Scherer and Wallbott, 1994), from which a textual corpus originated, which is frequently used in NLP. It consists of event descriptions and is therefore relevant for appraisal theories. Further, participants in that study have not only been asked to report on events they experienced, but they also report additional aspects, including the existence of bodily reactions. However, their work does not focus on the *linguistic realization* of emotion components, but on the *existence* in the described event.

Similarly, Troiano et al. (2019) asked crowdworkers to report on events that caused an emotion. This resource has then been postannotated with appraisal dimensions (Hofmann et al., 2020). This is the only recent work we are aware of that models appraisal as a component of the CPM to predict emotion categories, next to the rule-based classification approach by Shaikh et al. (2009), who built on top of the work by Clore and Ortony (2013). Another noteworthy related work is SenticNet, which models event properties including people's goals, for sentiment analysis (Cambria et al., 2014).

The only work we are aware of that studies emotion components (though not following the CPM, and without computational modelling), is the corpus study by Kim and Klinger (2019). They analyze if emotions in fan fiction are communicated via facial descriptions, body posture descriptions, the appearance, look, voice, gestures, subjective sensations, or spatial relations of characters. This set of variables is not the same as emotion components, however, it is related. They find that some emotions are preferred to be described with particular aspects by authors. Their work was motivated by the linguistic study of van Meel (1995).

In contrast to their work, our study compares two different domains (Tweets and Literature), and follows the emotion component process model more strictly. Further, we show the use of that model for computational emotion classification through multi-task learning.

3 Corpus Annotation

3.1 Corpus Selection

To study the relation between emotion components and emotions, we annotate subsets from two different existing emotion corpora from two different domains, namely literature and social media.

For literature, we use the REMAN corpus (Kim and Klinger, 2018), which consists of fiction written after the year 1800. It is manually annotated with text spans related to emotions, as well as their experiencers, causes, and targets. Emotion cue spans are annotated with the emotions of anger, fear, trust, disgust, joy, sadness, surprise, and anticipation, as well as 'other emotion'. From the 1720 instances, we randomly sample a subset of 1000. Each instance comprises a sentence triple and may contain any number of annotated spans. We map the emotions associated to spans to the text instances as the union of all labels, which leads to a multi-label classification task. Instances without emotion annotations are considered 'neutral'.

For the social media domain, we choose the Twitter Emotion Corpus (TEC) (Mohammad, 2012). The emotion categories are anger, disgust, fear, joy, sadness, and surprise. TEC consists of approximately 21,000 posts from Twitter that have a hashtag at the end which states one of the six mentioned emotions. According to the authors, the validity of hashtags as classification labels is commensurable to the inter-annotator agreements of human annotators. We randomly sample 2041 instances with the emotion hashtags as labels for the creation of our corpus. Each instance equals one post and has exactly one emotion label.

3.2 Annotation Procedure and Inter-Annotator Agreement

We annotate the emotion component dimensions independently: The existence of a CPM label means that this component is mentioned somewhere in the text, independent of its function to communicate one of the emotions. This is a simplification due to the fact that it turned out to be difficult to infer from the limited context of an instance if an emotion category and an emotion component mention are actually in relation. Further, this procedure also ensures that there is no information leak introduced in the annotation process (e.g., that components are only annotated if they indeed inform the emotion, and that a model could learn from its sheer presence).

Component	Explanation of Example	Example
Cognitive appraisal	evaluation of the pleasantness of an event.	Thinks that @melbahughes had a great 50th birthday party
Neurophysiol. symptoms	change in someone's heartbeat.	Loves when a song makes your heart race [...]
Motiv. Action tendencies	urge to attack a person or object.	sometimes when i think bout you i want to beat the shit out of your face so everyone can see how ugly you are inside and out
Motor expressions	facial expression.	@TheBodyShopUK when I walk in the room and my 9month old nephew recognises me and his face lights up with the biggest smile thats 100%
Subjective feelings	internal feeling state.	Feelin a bit sad tonight

Table 1: Excerpt of the final annotation guidelines including examples from TEC.

Component	round 1	round 2
Cognitive appraisal	0.288	0.777
Neurophysiological symptoms	0.459	–
Motiv. Action tendencies	0.444	0.732
Motor expressions	0.643	0.617
Subjective feelings	0.733	0.793

Table 2: Inter-annotator agreement after the different annotation rounds during the guideline creation process measured with Cohen's κ. In the second round, no annotator detected the neurophysiological component in the sample instances.

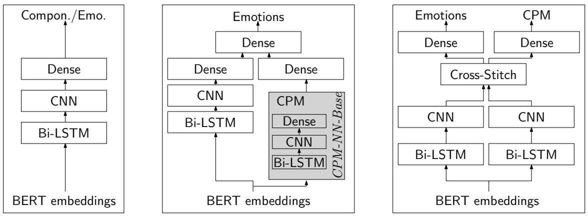
We refined the annotation guidelines in an iterative process with two annotators. Annotator 1 is a 23 year-old female undergraduate computer science student, Annotator 2 is a 28 year-old male graduate student of computational linguistics. We first defined a list of guidelines for each emotion component, then let each annotator label 40 randomly sampled instances (20 each in two iterations) out of each corpus and measured the inter-annotator agreement. Based on instances with disagreement, we refined the guidelines. The achieved inter-annotator agreement scores are displayed in Table 2. We observe that particularly the concepts of cognitive appraisal and motivational action tendencies have been clarified. During this process, for example, the discussion of the instance *"He did so, and to his surprise, found that all the bank stock had been sold, and transferred"* lead to the addition of a rule stating that the explicit mention of a feeling has to be annotated with subjective feeling. A rule for the annotation of tiredness as neurophysiological symptoms was created due to the instance *"Here he remained the whole night, feeling very tired and sorrowful."*. Concerning the annotation of verbal communication as motor expression, we decided to only annotate instances with verbal communications that address an emotional reaction or instances with interjections as for example 'oh' or 'wow'. With this clarification, the instance *"'Jolly rum thing about that boat,' said the spokesman of the party, as the boys continued their walk. 'I expect it got adrift somehow,' said another. 'I don't know,' said the first."* should not be annotated, whereas *"'Sounds delightful.' 'Oh, it was actually pretty cool.'"* should (this aspect has particularly appeared in the second annotator training round, which lead to a slight decrease in agreement). We make the annotation guidelines available together with our corpus. Table 1 shows a short excerpt.

After the refinement process concluded, Annotator 1 annotated the subsample of TEC and Annotator 2 annotated the subsample of REMAN.

3.3 Corpus Statistics

We show corpus statistics in Table 3 to develop an understanding how emotions are communicated in the two domains. For both corpora, we observe that cognitive appraisal is most frequent. In TEC, the second most dominant component is subjective feeling, while in REMAN it is the motor expression. The amount of subjective feeling descriptions is substantially lower for literature than for social media – which is in line with the show-don't-tell paradigm which is obviously not followed in social media as it is in literature.

Components are not distributed equally across emotions. Particularly noteworthy is the co-occurrence of disgust with neurophysiological symptoms in social media, but not in literature where this component dominates the emotion of fear. We also observe a particularly high co-occurrence of the subjective feeling component with fear for social media, which is not the case for literature. In literature, the motivational action tendency component co-occurs with anger (and anticipation) more frequently than with all other emotions. This is not the case for the social media do-



(a) *Emo/CPM-NN-Base* (b) *Emo-Cpm-NN-Pred* (c) *MTL-XS*

Figure 1: Neural Model Architectures (subset)

main. On the REMAN corpus, components occur least frequently when there is no emotion across all components. For both corpora, neurophysiological symptoms make up the smallest share of components, even more so in the case of TEC than REMAN.

In a comparison of social media and literature, we observe that emotions are distributed more uniformly in literature. The relative number of co-occurrences of CPM components with emotions varies more for REMAN than for the TEC corpus.

4 Methods

We will now turn to the computational modelling of emotion components and evaluate their usefulness for emotion classification. We evaluate a set of different feature-based and deep-learning based classification approaches to join the tasks of emotion classification and component classification.

4.1 Emotion Classifier

As baseline emotion classification models which are not particularly informed about components, we use two models: ***Emo-ME-Base*** is a maximum entropy (ME) classifier with TF-IDF-weighted bag-of-words unigram and bigram features. As preprocessing, we convert all words to lowercase, and stem them with the PorterStemmer. On TEC, with its single-label annotation, *Emo-ME-Base* consists of one model, while on REMAN with multi-label annotation, we use 10 binary classifiers.

Our neural baseline ***Emo-NN-Base*** uses pretrained BERT sentence embeddings[2] (Devlin et al., 2019) as input features. Inspired by Chen and Wang (2018); Sosa (2017), the network architecture consists of a bidirectional LSTM layer (Hochreiter and Schmidhuber, 1997), followed by a convolutional layer with kernel sizes 2, 3, 5, 7, 13, and 25. The outputs of the convolutional layer are max-pooled over the dimension of the input sequence, inspired by Collobert et al. (2011). Stacked on top of the pooling layer is a fully connected layer. Its outputs are finally fed into an output layer with a sigmoid activation function (see Figure 1a).[3]

We use dropout regularization after each layer. The network uses a weighted cross-entropy loss function, whereby the loss of false negatives is multiplied by 4 to increase recall. The model is trained using an Adam optimizer (Kingma and Ba, 2015). All network parameters of this model and subsequent neural models are determined using a subset of the training data as development set for the REMAN corpus and using 10-fold cross-validation for the TEC corpus. Details of the resulting hyperparameters are listed in the Appendix.

4.2 Component Classifier

The emotion component classifiers predict which of the five CPM components occur in a text instance. Our ***Cpm-ME-Base*** baseline models (one for each component) only use bag-of-words features in the same configuration as *Emo-ME-Base*.

In the model ***Cpm-ME-Adv***, we add task-specific features, namely features derived from manually crafted small dictionaries with words associated with the different components. Those dictionaries were developed without considering the corpora and with inspiration from Scherer (2005) and contain on average 26 items. Further, we add part-of-speech tags (calculated with spaCy[4], Honnibal et al. (2020)) and glove-twitter-100 embeddings[5] (Pennington et al., 2014). Additionally, only for the cognitive appraisal component, we run the appraisal classifier developed by Hofmann et al. (2020) and use the predictions as features.[6] For each component individually, the best-performing combination of these features is chosen.

The ***Cpm-NN-Base*** is configured analogously to *Emo-NN-Base*. The primary reason for using an equivalent setup is to facilitate a multi-head architecture as joint model for both tasks in the next step.

[2]https://tfhub.dev/google/experts/bert/wiki_books/sst2/1

[3]We selected this architecture based on preliminary experiments on the validation data. We evaluated it against LSTM-Dense Layer and CNN-LSTM architectures.

[4]https://spacy.io/usage/linguistic-features#pos-tagging

[5]https://nlp.stanford.edu/projects/glove/

[6]http://www.ims.uni-stuttgart.de/data/appraisalemotion

	Emotion	Cognitive		Phys.		Motiv. Action		Motor Exp.		Subject.		Total
TEC	Anger	127	(75%)	8	(5%)	30	(18%)	20	(12%)	49	(29%)	169
	Disgust	65	(83%)	11	(14%)	6	(8%)	17	(22%)	19	(24%)	78
	Joy	606	(71%)	59	(7%)	176	(21%)	95	(11%)	233	(27%)	848
	Sadness	323	(87%)	13	(3%)	58	(16%)	53	(14%)	142	(38%)	373
	Fear	196	(74%)	9	(3%)	37	(14%)	27	(10%)	130	(49%)	266
	Surprise	219	(71%)	2	(1%)	55	(18%)	55	(18%)	83	(27%)	307
	Total.	1536	(75%)	102	(5%)	362	(18%)	267	(13%)	656	(32%)	
REMAN	Anger	66	(67%)	7	(7%)	40	(41%)	61	(62%)	25	(26%)	98
	Anticip.	69	(59%)	6	(5%)	50	(43%)	63	(54%)	19	(16%)	117
	Disgust	81	(86%)	5	(5%)	21	(22%)	33	(35%)	16	(17%)	94
	Fear	96	(67%)	33	(23%)	35	(24%)	70	(49%)	34	(24%)	143
	Joy	121	(57%)	11	(5%)	28	(13%)	117	(55%)	66	(31%)	213
	Neutral	39	(34%)	0	(0%)	13	(11%)	22	(19%)	3	(3%)	116
	Other	64	(57%)	11	(10%)	21	(19%)	53	(47%)	21	(19%)	113
	Sadness	94	(69%)	19	(14%)	22	(16%)	66	(49%)	42	(31%)	136
	Surprise	103	(74%)	11	(8%)	21	(15%)	83	(60%)	22	(16%)	139
	Trust	94	(82%)	2	(2%)	17	(15%)	34	(30%)	27	(23%)	115
	Total	610	(61%)	76	(8%)	190	(19%)	440	(44%)	174	(17%)	

Table 3: Total/relative counts of CPM components and emotions in our reannoted TEC and REMAN subsamples. Note that the CPM categorization is a multi-label task, with 1000 instances in REMAN and 2041 instances reannotated in TEC.

4.3 Joint Modelling and Multi-Task Learning of Emotions and Components

To analyze if emotion classification benefits from the component prediction (and partially also vice versa), we set up several model configurations.

In ***Emo-Cpm-ME-Pred***, we predict the emotion with *Cpm-ME-Adv* and use these predictions as features. Other than that, *Emo-Cpm-ME-Pred* corresponds to *Emo-ME-Base*. In ***Emo-Cpm-ME-Gold***, we replace the predictions by gold component annotations to analyze error propagation.

Emo-Cpm-NN-Pred and ***Emo-Cpm-NN-Gold*** are configured analogously and follow the same architecture as *Emo-NN-Base* with the following differences: A binary vector with the CPM annotations is introduced as additional input feature, feeding into a fully connected layer. Its outputs are concatenated with the outputs of the penultimate layer and passed to another fully connected layer, followed by the output layer.

Emo-Cpm-NN-Pred uses *Cpm-NN-Base* to obtain component predictions, but the weights of *Cpm-NN-Base* are frozen. The basic network architecture resembles that of the *Emo-Cpm-NN-Gold* model, replacing the additional CPM input vector with the *Cpm-NN-Base* model (see Figure 1b). Its outputs are, again, fed into a fully connected layer which is connected to the output layer.

Next to the models that make use of the output of the CPM classifiers for prediction, we use two multi-task learning models which predict emotions and components based on shared latent variables. For a multi-head variant (***MTL-MH***), the basic architectures of the individual models for both tasks remain the same. Outputs of the CNN layer are fed to two separate, task-specific, fully connected layers. This model has two output layers, one for emotion classification and one for CPM component classification. Both tasks use the weighted cross entropy loss function to increase recall.

Based on the model proposed by Misra et al. (2016), we use cross-stitch units in our model ***MTL-XS***. This model employs two separate parallel instances of the *Cpm-NN-Base* architecture introduced above, one for the CPM classification task and one for emotion classification. The model additionally employs one cross-stitch unit after the respective CNN layers. This sharing unit learns a linear combination of the pooled task-specific CNN activation maps which is then passed to the task-specific fully connected layers. The cross-stitch unit learns during training which information to share across tasks (see Figure 1c).

5 Results

For our experiments, we use our reannotated subsample of TEC and REMAN (not all instances available in TEC and REMAN). We split the corpora into 90% for training and 10% to test.

	Component	*Cpm-ME-Base* P	R	F_1	*Cpm-ME-Adv* P	R	F_1	*Cpm-NN-Base* P	R	F_1	*MTL-XS* P	R	F_1	*MTL-MH* P	R	F_1
REMAN	Cognitive appraisal	60	98	**75**	60	98	**75**	60	98	**75**	60	98	**75**	59	96	73
	Neurophysiological symp.	50	20	29	50	40	**44**	20	20	20	25	20	22	0	0	0
	Motiv. action tendencies	36	47	41	46	68	**55**	42	26	32	29	42	34	25	68	36
	Motor expressions	67	56	61	76	65	**70**	92	53	68	76	60	68	81	60	69
	Subjective feelings	38	32	34	45	53	49	58	37	45	48	53	**50**	35	32	33
	Macro avg.	50	51	48	56	65	**59**	54	47	48	48	55	50	40	51	42
	Micro avg.			61			**67**			63			63			57
TEC	Cognitive appraisal	72	99	84	76	98	**86**	76	88	81	77	90	83	75	91	82
	Neurophysiological sympt.	17	17	17	15	33	21	25	17	20	17	17	17	100	17	**29**
	Motiv. action tendencies	42	57	48	50	74	**60**	46	51	49	48	57	52	45	54	49
	Motor expressions	47	52	49	41	61	49	55	58	**56**	50	48	49	62	32	43
	Subjective feelings	63	70	66	63	70	66	74	81	**77**	61	81	69	57	80	67
	Macro avg.	48	59	53	49	67	56	55	59	**57**	51	59	54	68	55	54
	Micro avg.			70			71			**73**			71			70

Table 4: Performance of the emotion component detection models (multiplied by 100).

5.1 Component Prediction

We start the discussion of the results with the component classification, a classification task that has not been addressed before and for which our data set is the first that becomes available to the research community. Table 4 shows the results.

The model performances are acceptable. Macro-average F_1 scores on REMAN range from .42 of *MTL-MH* to .59 for *Cpm-ME-Adv*, and from .53 (*Cpm-ME-Base*) to .57 (*Cpm-NN-Base*) on TEC. There are, however, differences for the components: On TEC, there are difficulties in predicting neurophysiological symptoms. The addition of task-specific features in *Cpm-ME-Adv* shows a clear improvement across all components.

The neural baseline *Cpm-NN-Base* outperforms *Cpm-ME-Adv* on TEC, and does so without feature engineering. On REMAN, the feature-based model is superior which might be due to the engineered features being more commonly represented in the literature domain than in social media. This is partially leveraged in the *MTL-XS* model on REMAN.

The components are not equally difficult to predict; the relations between the components are comparable across models. The lowest performance scores are observed for neurophysiological symptoms. This holds across models and corpora. For the neurophysiological component on the literature domain, however, the engineered features in *Cpm-ME-Adv* show substantial improvement, yielding an F_1 score of 0.44. Cognitive appraisal shows best prediction performances, with F_1 between .73 and .86. For TEC, we observe a correlation between performance and class size for all components.

For REMAN, *Cpm-ME-Adv* is the best-performing model. *Cpm-ME-Adv*'s macro average F_1 of 0.59 is 9pp higher than the second best F_1-score. For TEC, the best results are achieved by *Cpm-NN-Base* with a macro F_1 of 0.57.

5.2 Emotion Classification

In this section, we discuss the performance of our emotion classification models across different configurations. One question is how providing component information to them helps most. Table 5 shows the results for all experiments.

The comparison of *Emo-ME-Base* and *Emo-NN-Base* reveals that a pure word-based model is not able to categorize emotions in REMAN, due to the imbalancedness in this multilabel classification setup. This observation is in line with previous results (Kim and Klinger, 2018). The use of BERT's contextualized sentence embeddings leads to a strong improvement of 43pp (against a 0 F_1 for *Emo-ME-Base*). The performance of the ME models is comparably limited also on TEC, though this is less obvious on the micro-averaged F_1 due to the imbalancedness of the resource (.35 macro, .54 micro F_1).

Our main research question is if emotion components help emotion classification. In our first attempt to include this information as features, we see some improvement. On REMAN, *Emo-Cpm-ME-Pred* "boosts" from 0 to 6 F_1, on TEC we

	Model	Anger	Anticip	Disgust	Fear	Joy	Neutral	Other	Sadness	Surpr.	Trust	Macavg.	Micavg.
REMAN	*Emo-ME-Base*	0	0	0	0	0	0	0	0	0	0	0	0
	Emo-Cpm-ME-Gold	18	0	0	25	16	62	0	0	0	0	12	14
	Emo-Cpm-ME-Pred	0	0	0	12	15	0	0	0	0	14	4	6
	Emo-NN-Base	36	18	29	41	59	46	14	36	**71**	50	40	43
	Emo-Cpm-NN-Gold	56	22	28	37	68	71	15	39	50	60	45	45
	Emo-Cpm-NN-Pred	32	0	**33**	34	**71**	40	17	**52**	58	42	38	43
	MTL-MH	35	16	24	39	62	49	22	48	67	**56**	42	42
	MTL-XS	**38**	**24**	26	**47**	64	**54**	**37**	48	64	55	**46**	**47**
TEC	*Emo-ME-Base*	11		0	53	64			43	38		35	54
	Emo-Cpm-ME-Gold	11		0	59	66			40	43		36	55
	Emo-Cpm-ME-Pred	11		0	59	67			43	43		37	55
	Emo-NN-Base	**41**		44	56	69			51	39		50	57
	Emo-Cpm-NN-Gold	52		33	67	72			60	47		55	62
	Emo-Cpm-NN-Pred	32		0	59	70			53	44		43	56
	MTL-MH	17		**57**	53	**76**			53	**45**		50	58
	MTL-XS	34		50	**60**	73			**57**	44		**53**	**61**

Table 5: F_1 (/100) results across models and emotion categories. (empty cells denote that this category is not available in the respective corpus. The best scores (except the gold setting) are printed bold face.

observe an improvement by 1pp, to .55 F_1. The inclusion of predicted component information as features in the neural network model shows no improvement on REMAN or on TEC.

To answer the question if this limited improvement is only due to a limited performance of the component classification model, we compare these results to a setting, in which the predicted values are replaced by gold labels from the annotation. This setup does show an improvement with *Emo-Cpm-ME-Gold* to .14 F_1 on REMAN, which is obviously still very low; and no improvement on TEC. However, with our neural model *Emo-Cpm-NN-Gold*, we see the potential of gold information increasing the score for emotion classification to .45 F_1 on REMAN and .62 F_1 on TEC.

This is an unrealistic setting – the classifier does not have access to annotated labels in real world applications. However, in the (realistic) cross-stitch multi-task learning setting of *MTL-XS*, we observe further improvements: On REMAN, we achieve .47 F_1 (which is even slightly higher than with gold component labels), which constitutes an achieved improvement by 4pp to the emotion classifier which is not informed about components. On TEC, we achieve .61 F_1, which is close to the model that has access to gold components (.62). This is an improvement of 4pp as well in comparison to the model that has no access to components but follows the same architecture.

Particularly, we observe that models with component information perform better across all emotions, with the exception of surprise on the REMAN corpus and anger on the TEC corpus. We can therefore conclude that emotion component information does contribute to emotion classification; the best-performing combination is via a cross-stitch model.

A detailed discussion based on example predictions of the various models is available in the Appendix.

6 Conclusion and Future Work

We presented the first data sets (based on existing emotion corpora) with emotion component annotation. While Hofmann et al. (2020) has proposed to use the cognitive appraisal for emotion classification, they did not succeed to present models that actually benefit in emotion classification performance. That might be due to the fact that cognitive appraisal classification itself is challenging, and that they did not compare multiple multi-task learning approaches.

With this paper we moved to another psychological theory, namely the emotion component process model, and make the first annotations available that closely follow this theory. Based on this resource, we have shown that, even with a comparably limited data set size, emotion components contribute to emotion classification. We expect that with a larger corpus the improvement would be more substantial than it is already now. A manual introspection of the data instances also shows that the components indeed help. Further, we have seen that emotions are communicated quite differently in the two domains, which is an explanation why emotion classification systems (up-to-today) need to be developed particularly for domains of interest. We propose that future work analyzes further which information is relevant and should be shared across these tasks in multi-task learning models.

Further, we propose that larger corpora should be created across more domains, and also that multi-task learning is not only performed individually, but also across corpora. Presumably, the component information in different domains is not the same, but might be helpful across them.

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Ethical Considerations

We did not collect a new data set from individuals, but did reannotate existing and publicly available resources. Therefore, this paper does not pose ethical questions regarding data collection.

However, emotion analysis has the principled potential to be misused, and researchers need to be aware that their findings (though they are not in themselves harmful) might lead to software that can do harm. We assume that sentiment and emotion analysis are sufficiently well-known that users of social media might be aware that their data could be automatically analyzed. However, we propose that no automatic system ever does report back analyses of individuals and instead does aggregate data of anonymized posts. We do not assume that analyzing literature data poses any risk.

One aspect of our work we would like to point out is that, in contrast to other and previous emotion analysis research, we focus and enable particularly the analysis of implicit (and perhaps even unconcious) communication of emotions. That might further mean that authors of posts in social media are not aware that their emotional state could be computationally analyzed, potentially, they are not even fully aware of their own affective state. We would like to point out that automatically analyzing social media data without the explicit consent of the users is unethical at least when the user can be identified or identify themselves, particularly if they might not be aware of the details of an analysis system.

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A Ablation Study for Feature Based Maximum Entropy Classification Model of Emotion Components

Table 6 shows the performance scores if just one additional feature is enabled (while bag-of-words always remains available). It can be seen, that the most advantageous feature are word embeddings. On REMAN, *Cpm-ME-Adv* achieves a macro F1-score of 0.59 and a micro F_1-score of 0.67. On TEC, we have respective values of 0.56 and 0.71, with the high micro score resulting from cognitive appraisal being the best performing class while also being more than twice as frequent as any other component.

		Emo-ME-Base			Dictionaries			POS-tags			Embeddings			Appraisal prediction		
	Component	P	R	F_1	P	R	F_1	P	R	F_1	P	R	F_1	P	R	F_1
REMAN	Cognitive appraisal	60	98	75	60	98	75	57	73	64	60	88	72	60	98	75
	Neurophysiological symptoms	50	20	29	25	20	22	00	00	00	40	40	40	50	20	29
	Action tendencies	36	47	41	38	42	40	28	47	35	45	68	54	36	47	41
	Motor expressions	67	56	61	68	58	63	61	63	62	76	65	70	67	56	61
	Subjective feelings	38	32	34	44	37	40	32	37	34	45	53	49	38	32	34
	Macro avg.	50	51	48	47	51	48	36	44	39	53	63	57	50	51	48
	Micro avg.			61			62			52			65			61
TEC	Cognitive appraisal	72	99	84	72	99	83	74	98	84	76	97	85	72	99	84
	Neurophysiological symptoms	17	17	17	11	17	13	00	00	00	12	33	17	17	17	17
	Action tendencies	42	57	48	40	51	45	42	63	50	45	66	53	42	57	48
	Motor expressions	47	52	49	43	48	45	34	45	39	40	61	48	47	52	49
	Subjective feelings	63	70	66	62	68	65	62	65	64	58	65	61	63	70	66
	Macro avg.	48	59	53	46	57	50	42	54	47	46	64	53	48	59	53
	Micro avg.			70			69			68			69			70

Table 6: Overview over the single feature's impact in classification with *Cpm-ME-Adv*. Each column displays the classification results if only this column's feature is additionally to bag-of-words features, enabled. In the last column, the additional feature is only used for the prediction of cognitive appraisal, due to the classification assumption that the components can appear individually of each other in text.

B Detailed Emotion Results for Emotion Classification

The results table in the main paper did, for space reasons, only show F_1 scores. Table 7 present the complete results for the neural network, including precision and recall values.

		Emo-NN-Base			*Emo-Cpm-NN-Gold*			*Emo-Cpm-NN-Pred*			*MTL-MH*			*MTL-XS*		
	Emotion	P	R	F_1	P	R	F_1	P	R	F_1	P	R	F_1	P	R	F_1
REMAN	Anger	28	50	36	47	70	**56**	33	30	32	31	40	35	31	50	38
	Anticipation	18	18	18	19	27	22	0	0	0	12	27	16	17	36	**24**
	Disgust	20	56	29	20	44	28	24	56	**33**	16	56	24	18	44	26
	Fear	35	50	41	25	71	37	33	36	34	28	64	39	40	57	**47**
	Joy	47	77	59	74	64	68	70	73	**71**	65	59	62	57	73	64
	Neutral	40	55	46	100	55	**71**	29	64	40	35	82	49	38	91	54
	Other	33	9	14	50	9	15	17	18	17	15	45	22	29	55	**37**
	Sadness	27	53	36	31	53	39	50	53	**52**	37	67	48	44	53	48
	Surprise	65	79	**71**	41	64	50	53	64	58	55	86	67	47	100	64
	Trust	39	69	50	86	46	**60**	67	31	42	43	77	56	50	62	55
	Macro avg.	35	52	40	49	50	45	38	42	38	34	60	42	37	62	**46**
	Micro avg.			43			45			43			42			**47**
TEC	Anger	50	35	41	57	47	**52**	30	35	32	29	12	17	42	29	34
	Disgust	40	50	44	50	25	33	0	0	0	67	50	**57**	50	50	50
	Fear	65	50	56	86	55	**67**	73	50	59	48	59	53	54	68	60
	Joy	60	82	69	68	78	72	67	72	70	79	74	**76**	66	82	73
	Sadness	57	47	51	61	58	**60**	61	47	53	66	44	53	61	53	57
	Surprise	48	32	39	45	50	**47**	40	50	44	36	62	45	60	35	44
	Macro avg.	53	49	50	61	52	**55**	45	42	43	54	50	50	55	53	53
	Micro avg.			57			**62**			56			58			61

Table 7: Performance of the neural network emotion classifiers. The highest F_1 scores are printed bold face.

C Neural Network Parameters

Table 8 shows the network parameters that were determined during the development process of the neural models.

	Parameter	*Cpm-NN-Base*	*Emo-NN-Base*	*Emo-Cpm-NN-Gold*	*Emo-Cpm-NN-Pred*	*MTL-XS*	*MTL-MH*
REMAN	Bi-LSTM units	24	24	24	24	32 / 24	24
	CNN filters	10	10	16	16	12 / 10	16
	FC neurons (cpm)	128	—	96	64	128	128
	FC neurons (emo)	—	128	128	128	128	128
	FC neurons (comb.)	—	—	128	96	—	—
	Loss weight (emo)	—	4.0	6.0	4.0	7.8	7.8
	Loss weight (cpm)	1.5	—	—	—	1.5	1.5
	Task weight (emo)	—	1.0	1.0	1.0	0.75	0.75
	Task weight (cpm)	1.0	—	—	—	0.5	0.35
	Minibatch size	60	50	50	50	25	25
TEC	Bi-LSTM units	24	24	24	24	32/24	24
	CNN filters	32	32	32	32	24/24	32
	FC neurons (cpm)	32	—	—	64	128	32
	FC neurons (emo)	—	128	128	128	128	128
	FC neurons (comb.)	—	—	256	256	—	—
	Loss weight (emo)	—	1.0	1.0	1.0	1.0	1.0
	Loss weight (cpm)	1.0	—	—	—	1.0	1.0
	Task weight (emo)	—	1.0	1.0	1.0	0.75	0.5
	Task weight (cpm)	1.0	—	—	—	0.5	0.5
	Minibatch size	40	80	80	80	80	80

Table 8: Neural network parameters. In cases where multiple values are displayed, the first value refers to the emotion detection part of the network, while the second value refers to CPM detection.

D Discussion of Instances

We show examples in Table 9 where component information is helpful for emotion classification. Regarding the neural classifiers, *MTL-XS* generally tends to predict fewer false positives when there are no strong correlations among the potential emotions to the predicted CPM, like in (1). Similarly, in (2) the model predicts only 'fear', which is more likely to occur together with the 'subjective feeling' component than 'anger' or 'disgust', according to Table 3 in the paper. Additionally, CPM information helps to solve ambiguities: In (3), the model predicts 'anticipation' rather than 'sadness', presumably because of the stronger correlation to the predicted CPM component 'action tendency'.

In the two TEC examples (4–5), the baseline detects 'joy', while *MTL-XS* correctly detects 'sadness'. The cross-stitch model predicts a 'subjective feeling' component in both instances and a 'cognitive appraisal' component in one instance. Both components are more strongly correlated with 'sadness' than with 'joy' (see Table 3 in main paper).

We also show some examples that exemplify differences in prediction of the ME-based models (6–8). Generally, the CPM information leads to little improvement in emotion detection on TEC. Nevertheless, there are some cases in which the correct emotion was predicted by at least one of *Emo-Cpm-ME-Gold* and *Emo-Cpm-ME-Pred*, whereas it was not detected by *Emo-ME-Base*. In both examples (6–7), the correct emotions 'surprise' and 'sadness' have not been found by *Emo-ME-Base* (predicting 'joy' and 'surprise' respectively). *Emo-Cpm-ME-Gold* and *Emo-Cpm-ME-Pred* both correctly predicted 'surprise' for (6) and 'sadness' for (7). There are indications of 'subjective feeling' in the second and of 'motor expression' and 'cognitive appraisal' in both examples, that were also predicted by *Cpm-ME-Adv*, which might have helped assigning the correct emotion class. On REMAN, the ME models were able to classify a small fraction of the instances correctly, which is still an improvement compared to the miserably failing baseline. An example with improved prediction for REMAN is (8), where the emotion 'joy' was correctly identified by *Emo-Cpm-ME-Gold* and *Emo-Cpm-ME-Pred*, while not being detected by *Emo-ME-Base*.

(1) As for the hero of this story, 'His One Fault' was absent-mindedness. He forgot to lock his uncle's stable door, and the horse was stolen. In seeking to recover the stolen horse, he unintentionally stole another. (REMAN)	
Emotion *Emo-NN-Base*	disgust, other, sadness
CPM, *MTL-XS*	**cognitive appraisal**
Emotion, *MTL-XS*	**neutral**
CPM Gold	**cognitive appraisal**, action tendency
Emotion Gold	**neutral**
(2) In that fatal valley, at the foot of that declivity which the cuirassiers had ascended, now inundated by the masses of the English, under the converging fires of the victorious hostile cavalry, under a frightful density of projectiles, this square fought on. It was commanded by an obscure officer named Cambronne. At each discharge, the square diminished and replied. (REMAN)	
Emotion *Emo-NN-Base*	anger, disgust, **fear**
CPM, *MTL-XS*	**cognitive appraisal**, subjective feeling
Emotion, *MTL-XS*	**fear**
CPM Gold	**cognitive appraisal**
Emotion Gold	**fear**
(3) If sleep came at all, it might be a sleep without waking. But after all that was but one chance in a hundred: the action of the drug was incalculable, and the addition of a few drops to the regular dose would probably do no more than procure for her the rest she so desperately needed.... She did not, in truth, consider the question very closely–the physical craving for sleep was her only sustained sensation. Her mind shrank from the glare of thought as instinctively as eyes contract in a blaze of light–darkness, darkness was what she must have at any cost. (REMAN)	
Emotion *Emo-NN-Base*	sadness, **fear**
CPM, *MTL-XS*	**cognitive appraisal**, **action tendency**
Emotion, *MTL-XS*	**fear**, **anticipation**
CPM Gold	**cognitive appraisal**, neurophysiological symptoms, **action tendencies**
Emotion Gold	**fear**, **anticipation**
(4) @justinbieber nocticed a girl the first day she got a twitter! :((TEC)	
Emotion *Emo-NN-Base*	joy
CPM, *MTL-XS*	**cognitive appraisal**, **subjective feeling**
Emotion, *MTL-XS*	**sadness**
CPM Gold	**cognitive appraisal**, **subjective feeling**
Emotion Gold	**sadness**
(5) when the love of your life is half way acrosss the world (TEC)	
Emotion *Emo-NN-Base*	joy
CPM, *MTL-XS*	**subjective feeling**
Emotion, *MTL-XS*	**sadness**
CPM Gold	**cognitive appraisal**
Emotion Gold	**sadness**
(6) My sister is home! YAY. VISIT (TEC)	
CPM *Cpm-ME-Adv*	**cognitive appraisal, motor expression**
Emotion *Emo-ME-Base*	joy
Emotion *Emo-Cpm-ME-Pred*	**surprise**
Emotion *Emo-Cpm-ME-Gold*	**surprise**
CPM Gold	**cognitive appraisal, motor expression**
Emotion Gold	**surprise**
(7) @lauren_frost It was?!?! What the heck, man! I always miss it! Haha. - You guys need another reunion!! :) (TEC)	
CPM *Cpm-ME-Adv*	**cognitive appraisal, motor expression, subjective feeling**
Emotion *Emo-ME-Base*	surprise
Emotion *Emo-Cpm-ME-Pred*	**sadness**
Emotion *Emo-Cpm-ME-Gold*	**sadness**
CPM Gold	**cognitive appraisal, motor expression, subjective feeling**
Emotion Gold	**sadness**
(8) And if this was a necessary preparation for what, should follow, I would be the very last to complain of it. We went to bed again, and the forsaken child of some half-animal mother, now perhaps asleep in some filthy lodging for tramps, lay in my Ethelwyn's bosom. I loved her the more for it; though, I confess, it would have been very painful to me had she shown it possible for her to treat the baby otherwise, especially after what we had been talking about that same evening. (REMAN)	
CPM *Cpm-ME-Adv*	**cognitive appraisal**, action tendency, **subjective feeling**
Emotion *Emo-ME-Base*	/
Emotion *Emo-Cpm-ME-Pred*	**joy**
Emotion *Emo-Cpm-ME-Gold*	**joy**
CPM Gold	**cognitive appraisal, subjective feeling**
Emotion Gold	disgust, **joy**, sadness, trust

Table 9: Examples in which components support emotion classification.